

Ontology based Framework for Conceptualizing Human Affective States and their Influences

by

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Abstract

The study of human affective states and their influences has been a research interest in psychology for some time. Fortunately, the presence of an affective computing paradigm allows us to use theories and findings from the discipline of psychology in the representation and development of human affective applications.

However, because of the complexity of the subject, it is possible to misunderstand concepts that are shared via human and/or computer communications. With the appearance of technological innovations in our lives, for instance the Semantic Web and the Web Ontology Language (OWL), there is a stronger need for computers to better understand human affective states and their influences. The use of an ontology can be beneficial in order to represent human affective states and their influences in a machine-understandable format. Truly, ontologies provide powerful tools to make sense of data.

Our thesis proposes HASIO, a Human Affective States and their Influences Ontology, designed based on existing psychological theories. HASIO was developed to represent the knowledge that is necessary to model affective states and their influences in a computerized format. It describes the human affective states (Emotion, Mood and Sentiment) and their influences (Personality, Need and Subjective well-being) and conceptualizes their models and recognition methods. HASIO also represents the relationships between affective states and the factors that influence them. We surveyed and analyzed existing ontologies regarding human affective states and their influences to realize the significance and profit of developing our proposed ontology (HASIO).

We follow the Methontology approach, a comprehensive engineering methodology for ontology-building, to design and build HASIO.

An important aspect in determining the ontology scope is Competency Questions (CQs). We configure HASIO CQs by analyzing the resources from psychology theories, available lexicons and existing ontologies.

In this thesis, we present the development, modularization and evaluation of HASIO. HASIO can profit from the modularization process by dividing the whole ontology in self-contained modules that are easy to reuse and maintain. The ontology is evaluated through Question Answering system (HASIOQA), a task-based evaluation system, for validation. We design and develop a natural language interface system for this purpose. Moreover, the proposed ontology was evaluated through the Ontology Pitfall Scanner for verification and correctness against several criteria.

Furthermore, HASIO was used in sentiment analysis on different Twitter dataset. We designed and developed a tweet polarity calculation algorithm. Additionally, we compare our ontology result with machine learning technique. We demonstrate and highlight the advantage of using ontology in sentiment analysis.

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Chapter 1

Introduction

The vision of digital twin as introduced by Prof. El Saddik (IEEE MultiMedia ¹, Volume: 25, Issue: 2, Apr.-Jun. 2018) is a digital replication of a living or non-living physical entity. By bridging the physical and the virtual worlds, data are transmitted seamlessly, allowing virtual and physical entities to exist simultaneously. A digital twin facilitates the means to monitor, understand, and optimize the functions of the physical entity and provides continuous feedback to improve quality of life and wellbeing. In essence, it is the convergence of several technologies, such as AI, AR/VR and Haptics, IoT, Cybersecurity and Communication networks.

One component of the digital twin vision is to build an ontology for Human Affective States and their Influences (HASIO) in order to ease the understanding, sharing and integration of data between systems. An ontology is considered to be the backbone of the Semantic Web. The objective of the Semantic Web is to permit a massive amount of web-accessible information to be used in an effective way by both humans and automated tools. It permits systems to access and understand structured collections of information [23]. Ontologies provide unified and semantic vocabularies for a domain and can be used by many applications in a specific domain [92]. In effort to harness the power of the Semantic Web and of ontologies, this thesis presents the development of HASIO, which will be used to represent human affective states and their influences.

1.1 Motivation

The Internet and the enormous volume of available data generate a strong request for data-sharing in a semantic manner. The use of ontologies has become essential for applications in many do-

¹<https://ieeexplore.ieee.org/xpl/RecentIssue.jsp?punumber=93>

mains. Ontologies capture domain knowledge to be used for specific applications, ease communication and data-sharing processes between applications, and integrate information from different resources, such as psychological theories and semantic lexicons.

The quantity of Internet data that is created by users each day is quite astonishing, which is why the development of ontologies that create a shared environment is so important. It allows computers and humans to gain a better understanding of data and therefore increases efficiency.

Ontologies allow devices and humans to understand data from the same point of view and to use vocabulary that has the same semantic meaning. They also function to solve communication problems between applications across different organizations. An ontology that can map different concepts and the semantic correspondence between them allows communication between applications that were not initially designed to collaborate [174].

There are strong relations between human affective states and their influences. Indeed, human behavior is impacted by emotion, mood, personality, needs and subjective well-being (SWB). Affective states are the experiences or feelings that a person can have. These states have influences that impact the type of feeling or experience that occurs. Emotion, mood and sentiment are human affective states, while personality, needs and subjective well-being are influences on those affective states. Accordingly, it is valuable to represent the human affective states and their influences in one ontology.

Great effort has been made toward building ontologies that detect and annotate emotions, while few target mood and human influence. We believe that investigating ontologies for mood, sentiment, needs and personality, as has been done with emotion, is an interesting avenue for future research. It would allow for the representation of these concepts and the relationships between them in an ontology. This would provide a standardized terminology for the affective states and their influencers, and facilitating interoperability between systems and people [25].

Subjective Well-Being (SWB) corresponds to human life satisfaction, which in turn leads to positive emotion and good mood. It is thus an important influence factor on human affective states. After exploring existing ontologies to the best of our abilities, we did not find any that represented SWB. We believe that creating an ontology for SWB will contribute significantly to increased comprehension of a person's mood and emotion [47].

Moreover, the Big Five personality trait theory is quite popular in academic research and must therefore be represented in an ontological format.

This thesis aims to provide shared and interoperable computerized representation that allows systems to better understand and conceptualize human affective states (emotion, mood, sentiment) and their influences (needs, SWB, personality).

1.2 Problem Statement and Proposed Solution

Currently, human and computer applications often involve communication and knowledge sharing. However, people express themselves in their own language using different terms and meanings. Users come from varying backgrounds and applications may be derived from systems not designed to communicate with each other. They may use terms with alternate meanings, causing misunderstanding. Without a doubt, the Internet necessitates a need for the sharing of data semantics. Moreover, the Internet transformed isolated devices into network-communicated devices. This transformation created a need for data to be shared and represented in a machine-understandable and processable format [71].

One key area that requires data sharing and processing is the domain of human affective states and their influences. This domain is complex and psychophysiological, composed of different models. Due to the complexity of human affective states and their influences, it is possible for misunderstandings to occur. Therefore, we must reduce or eliminate conceptual and terminological confusion and come to a shared understanding. Ambiguous problems can be faced by representing and understanding different models of human affective states and their influences.

The use of different models leads to problems of data interoperability and integration [41]. so there is a compelling need for the domain to be understood and represented in a computerized and unified way.

The domain of human affective states and their influences is updated continuously with psychological findings, so it is a valuable method of easily extending representation rather than starting the process a new each time. This thesis presents how human affective states and their influences can be studied in a way that is efficient for both people and their devices.

Ontologies aim to unify terms and meanings in order to enable effective communication between people and computers. They capture knowledge and provide a generally accepted understanding of a given domain. The study of human emotions, moods, sentiments, needs, personality, and SWB is significant, as these concepts have a big impact on behaviors. Building an ontology for this domain allows us to create a semantic application. Constructing an application on top of an ontology facilitates information sharing and communication between systems in a meaningful manner [174]. The use of Web Ontology Language (OWL) allows us to create an ontology that is readable by machines and humans, as well as having reasoning and inference capabilities.

Human Affective States and their Influences Ontology (HASIO) contains many axioms to cover the representation of human affective states and their influences. Consequently, dividing HASIO into modules makes the job of reusing, maintaining and understating our ontology much easier. Modularized HASIO is more accessible for a particular application.

The evaluation process determines the quality of the ontology and correctness according to specific criteria. In our work, we evaluated HASIO for validation and verification. For the former, we used Question Answering (HASIOQA): a task-based evaluation system to validate that the major requirements of the ontology were satisfied. For the latter, we used OOPS!, a web-based tool that scans for major pitfalls. We also verified HASIO's consistency by running a Pellet reasoner.

Interestingly, and with great benefit to HASIO, an ontology can be scaled to import additional ontologies into the same domain. As a result, more information can be added to enhance it. This feature is called "ontology reusing," allowing HASIO to be easily updated and added to with further knowledge.

Furthermore, we demonstrate that an ontology is a good tool for sentiment analysis, compared with machine learning techniques as presented in Chapter 6.

To accomplish our proposed solution, in this thesis we :

- Survey and analyze existing ontologies regarding human affective states and their influences
- Develop Human Affective States and their Influences Ontology (HASIO)
- Analyze resources from psychology theories, available lexicons and existing ontologies to configure HASIO CQs
- Modularize HASIO
- Design and development:
 - HASIO Natural Language Interface System
 - Tweet polarity calculation algorithm to employ HASIO into sentiment analysis

1.3 Thesis Organization

The remainder of this thesis is organized as follows: Chapter 2 provides background on ontologies and on affective states and their influences. Chapter 3 presents existing affective state ontologies and their influences. We discuss the development and conceptualization of the HASIO in Chapter 4. An evaluation of HASIO is provided in Chapter 5. Chapter 6 we present a case study based on HASIO: sentiment analysis on Twitter. Finally, in Chapter 7 we draw our conclusions.

1.4 Scholarly Achievements (Published \Accepted)

- Rana Abaalkhail, Fatimah Alzamzami, Samah Aloufi, Rajwa Alharthi, and Abdulmotaleb El Saddik, "Affectional Ontology and Multimedia Dataset for Sentiment Analysis", Accepted by International Conference on Smart Multimedia (ICSM)2018, Toulon, France.
- Rana Abaalkhail, Benjamin Guthier, Rajwa Alharthi, and Abdulmotaleb El Saddik, "Survey on Ontologies for Affective States and their Influences", Semantic Web journal, pages 1-18 (2017).
- Benjamin Guthier, Rana Abaalkhail, Rajwa Alharthi, Abdulmotaleb El Saddik, "The Affect-Aware City", In Proceedings of the 2015 International Conference on Computing, Networking and Communications (ICNC 2015), Anaheim, California, USA, February 16-19, 2015 , pages 630-636.
- Benjamin Guthier, Rajwa Alharthi, Rana Abaalkhail and Abdulmotaleb El Saddik, "Detection and Visualization of Emotions in an Affect-Aware City", In Proceedings of the 1st International Workshop on Emerging Multimedia Applications and Services for Smart Cities (EMASC-2014), Nov, 7, 2014, Orlando, Florida, USA, pages 23-28.

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Chapter 2

Background

In this chapter we discuss the background of ontologies as well as that of affective states and their influences, before moving on to HASIO's conceptualization and design. Section 2.1 explains the background of ontology, which consists of: definition 2.1.1, types of ontologies 2.1.2, ontology components 2.1.3, Semantic Web and ontology 2.1.4, linked data and the Semantic Web 2.1.5, ontology language 2.1.6, ontology operation 2.1.7, and ontology evaluation 2.1.9.

Section 2.2 provides a background on affective states and their influences, including the following: affective states 2.2.1, the influences of affect 2.2.2, the relationships between affective states and their influences 2.2.3, recognition methods for affective states and their influences 2.2.4, emotion expression cues 2.2.5, and the causes of emotion and mood 2.2.6.

2.1 Background on Ontologies

With the vast quantity of information that is now available to us, there should be a well-organized way to retrieve and interpret it. Information retrieval (IR) and ontologies are both used for information discovery. IR suffers from weak representation with regard to concepts and relations, while ontologies represent these aspects strongly. As a result, ontologies can have stronger reasoning abilities. Although IR adopted strong statistical methods, it does not handle larger amounts of information well [49].

Ontologies can eliminate the drawbacks of IR since they can retrieve information based on inference functions. IR is dependent upon a keyword-based model, which limits the searching and retrieving of information. By contrast, ontologies search by meaning [49].

Building an ontology is done to represent a unified domain vocabulary in a semantic and machine-understandable format. This can help facilitate communication between people and computers. As a result, ontologies have become popular in many areas, such as web technologies and natural language processing. Indeed, ontologies are the core of the Semantic Web.

2.1.1 Ontology Definition

An ontology can be seen as a catalog that shows entities in a specific field and the relationships between them. It represents structural knowledge for any domain and defines a common vocabulary to be shared. In addition, it defines data and data structures to be used in applications within the same field [133]. An ontology is defined as "an explicit specification of a conceptualization" [79]. Borst [29] gave another definition of ontology as "a formal specification of a shared conceptualization." The latter definition highlights two characteristics of ontologies: formal and conceptualization. "Formal" means that the ontology should be expressed in a machine-readable format, while the "conceptualization" means that the ontology should express the shared view of domain experts rather than an individual view.

In essence, an ontology is a type of knowledge representation used by knowledge-based systems that store and reason about information that model the real world domain [166].

There are many examples that demonstrate the need for ontologies [133] :

- Enable a common understanding of a domain between people and software
- Enable domain knowledge reusing
- Remove the ambiguity of domain assumptions
- Enable domain knowledge analysis

Ontologies can unite terms that are used on different websites, such as medical webpages. Moreover, general ontologies (top-level) can be used in many domains. Using ontologies facilitates the acceptance of a domain assumption and eases the modification process. They can also be used in different situations, such as problem-solving and domain applications, software agents, as well as between a system and different applications [133].

Ontologies play a key role in the Semantic Web and in Artificial Intelligence (AI) with regard to the exchange of information in various environments. They can also be used in multi-agent systems, where agents use the ontology as a reference for easy and accurate communication between each other. Search engines use ontologies as well, in order to find synonyms of search terms [174]. For example, estimating student emotions during e-learning sessions can be achieved by

using an ontology technique [57]. Another example is an avatar that is capable of showing appropriate facial expressions and gestures, that are selected based on an ontology that represents emotions associated with facial expressions and gestures [69].

The ability to reuse an ontology is considered to be a significant and valuable feature of ontology engineering. Reuse can occur at the top level of an ontology, of a smaller section, or by extending an existing one [27]. In addition, developers are able to adopt an ontology to serve in another domain. Reusing an existing ontology is much less time-consuming than creating a new one, as it has already been tested and therefore ensures a certain level of quality for the new ontology. Moreover, it allows for mapping between ontologies and improves the maintainability of new ones [61].

2.1.2 Types of Ontologies

Although ontologies represent the real world in a computerized format, their conceptualization can vary depending on the aspect of the real world in which we are interested. Consequently, there are different types of ontologies, which can be identified based on their generality level [169]:

- Generic ontology: also known as a top-level ontology or a core ontology. It can be used across several domains.
- Domain ontology: represents the terms and relationships for a particular domain. This kind of ontology is valid for one specific domain.
- Application Ontology: covers the knowledge required for a specific application. It represents the information needed to solve a specific problem.

Ontologies can also be distinguished by their level of formality. They can be informal and therefore expressed in natural language, or formal, where terms are defined with formal semantics [180].

In addition, ontologies can be described by other characteristics, for example, as lightweight and heavyweight. Lightweight ontologies include concepts, relationships and properties, while a heavyweight ontology adds axioms and constraints[174].

2.1.3 Ontology Components

Ontologies include major components: classes, instances, object properties and axioms that are used to represent information in a semantic manner [174]

Classes are the focal point of ontologies; they describe the concepts in a domain. They can be arranged in a subclass-superclass hierarchy, which can also be called a child class and parent class. A class represents a group of different individuals that share similar characteristics. Classes are also referred to as concepts.

An instance of a class is called an individual and it represents a specific object of a class.

Object properties describe the semantic relationship between individuals. The first individual belongs to the domain and the second individual belongs to the range. Object properties can also be called slots. Moreover, an axiom is used to enforce restrictions on the values of classes or instances.

Axioms can say something about class individuals and properties, e.g., `Male rdfs:subClassOf:Person` is a class axiom.

A class can be presented as Defined or Primitive [91]. Defined class has necessary and sufficient conditions, and is introduced in Web Ontology Language (OWL) with equivalent classes axiom. For example, If class `Person` that in Figure 2.1 has subclass `University_Student` that is equivalent to the condition: the intersection between `Person` and the restriction `studiesIn some University`. This implies that if an individual is a member of `University_Student` then it must satisfy the conditions, and if an individual satisfies the conditions then the individual must be a member of `University_Student`.

By contrast, Primitive class only has necessary conditions and is introduced in OWL with subclass axiom; for example: class `Person` that in Figure 2.1 has axiom as: `hasIDIn some University` (defined as necessary condition). This implies that if an individual is a member of `Person` then it must satisfy the conditions. However, if an individual satisfies the necessary conditions, we cannot say that they are a member of `Person`; perhaps an organization has ID in the university. As a result, the organization is not an individual of the class `Person`.

In addition, an ontology has data properties that link individuals to data values. For example, `Marry` has age 20.

```
:Marry rdf:type owl:NamedIndividual ;
:age "20" ^^^xsd:int.
```

Classes, properties and individuals are called entities. Figure 2.1 shows a representation of an ontology and its components. For instance, *person* is a class, *Jon* is an individual, and *studiesIn* is an object property.

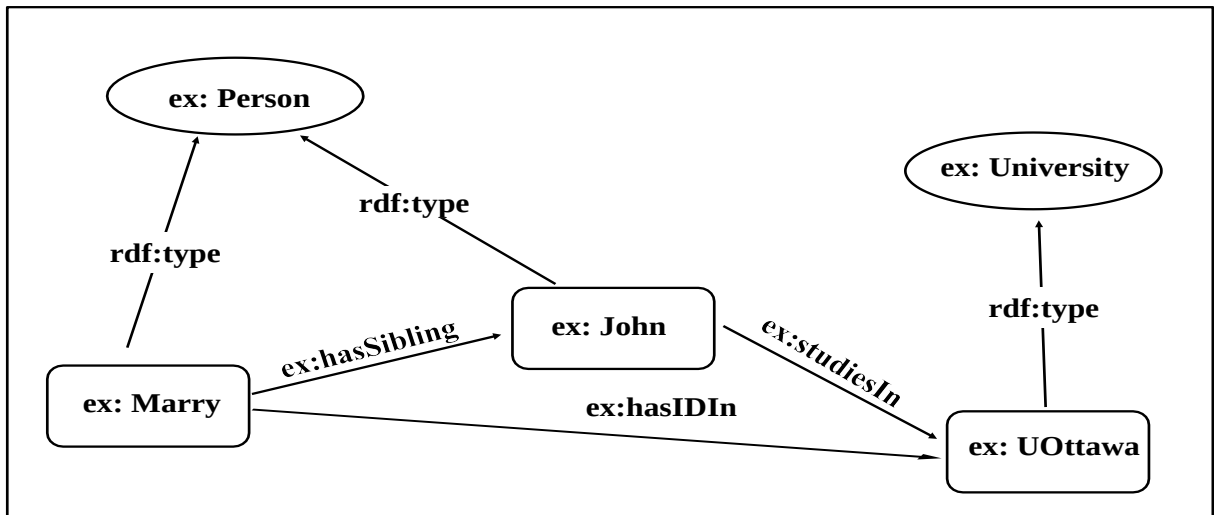


Figure 2.1: Representation of ontology components. Oval shapes represent classes, rounded rectangles represent individuals, and arrows indicate object properties.

2.1.4 Semantic Web and Ontology

The Semantic Web aims to provide information that can be used by machines and not just for the purpose of display. The idea is to enable computers to use information for automation, integration and reuse across applications. The Semantic Web modifies the web from machine-readable to machine-understandable. Ontologies are the basis of the Semantic Web, allowing knowledge representation and sharing. They describe data semantics and represent domain concepts as well as the relations between them [115]. Figure 2.2 illustrates the architecture of the Semantic Web. It consists of many languages stacked into layers. Each language extends the language of the layers below. The bottom layer is **Uniform Resource Identifier (URI)**, which is a unique name for each resource on the web. The next layer is **eXtensible Markup Language (XML)**, which provides the base for Semantic Web language. XML uses tags to deliver extra information about text; it is hierarchically structured with no semantics. It provides a stranded syntax that can be used by the languages in the next layers. URI and XML represent the normal web.

On top of XML comes **Resource Description Framework (RDF)**, which is the first layer in the Semantic Web. It offers a simple graph reference model that consists of nodes and binary relations. RDF has many syntaxes and one of them is XML (RDFXML).

RDF is a data model represented as a graph, while XML represents the data as a tree.

Then, **RDF Schema (RDFS)** goes on top of RDF. It offers a simple vocabulary and axioms for

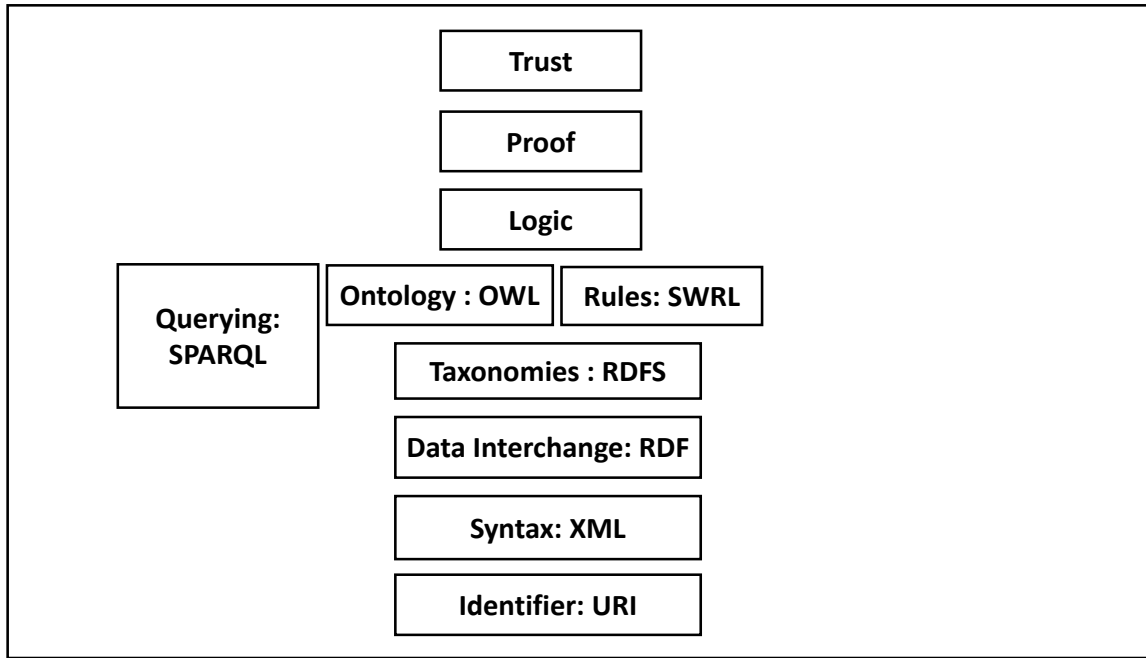


Figure 2.2: Semantic Web Stack

object-oriented modeling. RDF provides a data model, while RDFS provides a structure for describing things; however, it does not have any noteworthy semantics. RDFS does not have many restrictions for the writing of RDF triples (subject, predicate, object), which causes confusion and difficulty in understanding the data description. Above RDFS we find (**OWL**), which offers an extra knowledge-base-oriented ontology construction. OWL provides a more advanced schema for data representation [48], [87].

XML has the power to exchange data, while OWL has the power to exchange information. RDF and OWL are both Knowledge Representation Languages (KR) [179], but RDF is based on binary relations while OWL is based on description logic. As a result, OWL provides richer representation for a class, property and axiom to model the world. OWL provides a way to model complex classes and axioms in order to reason about ontology data [12].

In addition, the Semantic Web stack contains **semantic rule**, sitting side by side with OWL (ontology). The Semantic Web Rule Language (SWRL) can be combined with OWL to provide reasoning about ontology concepts. Using SWRL with an ontology allows for greater expression and decidability [93]. Along with RDF and OWL, there is also SPARQL, which is a query language.

The last three layers of the Semantic Web architecture are: **Logic, Proof and Trust**. In the Semantic Web, the building of systems follows a logic that reflects the structure of an ontology. A reasoner is used to check and resolve consistency issues; it also has the ability to make new inferences. Trust is the final layer of the Semantic Web and it concerns the trustworthiness of the information on the web, aiming to guarantee the quality of it [174].

2.1.5 Linked Data and the Semantic Web

The Semantic Web is a network of linked data from different web resources. Berners-Lee defines rules about publishing data on the web: use URIs to name items, use Hypertext Transfer Protocol (HTTP) URIs to look items up, and use RDF and a query language (SPARQL) to model and query the data ¹. These rules have become linked data principles. Linked data depends on two technologies: URIs and HTTP protocol, where the former is used to look up items using the latter. The link between resources is encoded using an RDF model: subject, predicate, object. The subject and object are both URIs that label a resource, and the predicate presents the relations between the subject and the object. In addition, the predicate is represented by a URI [26]. For example, to link a person's profile from the Friend Of A Friend ontology (FOAF) with their information in DBpedia ² is a knowledge base that serves as linked data on the Web. It is a project with the purpose of extracting structured content from information created in Wikipedia [109] -

we can have

```
<http://www.w3.org/People/Berners-Lee/card#i>
```

Owl: sameAs

```
<http://dbpedia.org/resource/Tim_Berners-Lee> ;
```

This example shows the link between the Berners-Lee profile in FOAF and DBpedia. Same As (predicate) links subject (<http://www.w3.org/People/Berners-Lee/card#i>) with object (http://dbpedia.org/resource/Tim_Berners-Lee).

2.1.6 Ontology Language

OWL is a machine-processable language and an international standard for coding and exchanging ontologies. It is designed to support the Semantic Web concept, which states that information should be given clear meaning to ensure that machines can process it more intelligently. As a

¹<http://www.w3.org/DesignIssues/>

²<http://wiki.dbpedia.org/services-resources/ontology>

```

DL:
Women  $\sqsubseteq$  Person
OWL:
###
http://www.semanticweb.org/rana-/ontologies/2018/0/
Human#Person
:Person rdf:type owl:Class
###
http://www.semanticweb.org/rana-/ontologies/2018/0/
Human#Women
:Women rdf:type owl:Class ;
rdfs:subClassOf :Person .

```

Figure 2.3: An example in DL and its corresponding OWL axiom.

result, computers have the ability to reason about the ontology. OWL is designed to be compatible with XML and is the extension of RDF and RSFS. Semantic Web languages such as RDF and OWL have the elasticity to represent and modify domain knowledge. OWL is based on a Description Logic (DL), which is a knowledge representation language used to represent domain knowledge in a structured way. Together, DL and OWL can provide clarity with semantic accuracy [14]. Figure 2.3 shows an example of a logical statement and the corresponding OWL classes: Women is a subclass of Person.

OWL consists of three languages: OWL Lite, OWL DL and OWL Full. Each of these allows developers to create classes, properties and individuals. However, OWL Lite and OWL DL have greater limitations. OWL Lite is meant for users with simple modeling constraint features, such as the cardinality of 0 and 1, while OWL DL has greater capabilities for expressive description and representation. However, OWL DL requires a resource to be either a class, an object property, a datatype property or an instance, while a resource cannot be a class and instance at the same time. OWL Full is suited for users that require maximum expressiveness with loose restrictions. In this version of the language, a class can be an instance simultaneously [87].

2.1.7 Ontology Operations

There are several operations that can be performed on ontologies [174]:

- **Ontology Transformation and Translation:** Ontology transformation is the process used to develop an ontology that must meet new requirements, while ontology translation is the

process of changing the structure of an ontology for a different purpose than originally intended.

- **Ontology Merging and Integration:** Ontology merging is the process of creating a new, single ontology from two or more existing ontologies of the same domain, while ontology integration is the process of creating a new, single ontology from two or more existing ontologies of different domains.
- **Ontology Mapping:** Ontology mapping is the process of defining the semantic relations between entities from different ontologies.

2.1.8 Ontology and Semantic Web Rule Language (SWRL)

Ontologies express concepts and describe relationships with each other as well as those with individual entities. However, on account of decidability, the expressiveness of ontology languages is restricted. Fortunately, ontologies can be further extended by a set of rules based on logic programming. SWRL³ was proposed to overcome this issue. It is set above ontology in the Semantic Web Architecture. Ontology is based on description logic in order to describe concepts, relations and assertions. Conversely, SWRL is based on logic programming, which is a set of sentences formalized in a logic form. SWRL expresses rules in terms of OWL concepts (classes, properties, individuals) and depends on a combination of OWL DL and OWL Lite sublanguages. SWRL is modeled on the concept antecedent (body) and consequent (head); this means that each time the conditions are stated in the antecedent grasp, the conditions specified in the consequent must also grasp. For example, to express "a child has a parent, the parent has a brother, and therefore the brother is the child's uncle" as a statement in SWRL, it would be:

```
hasParent (?x1, ?x2) , hasBrother (?x2, ?x3) -> hasUncle (?x1, ?x3)
```

The above SWRL rule contains the antecedent and the consequent and holds a combination of atoms. The execution of the rule results in the individual mapped to variable x1 to have the relationship property hasUncle with the individual mapped to variable x3 [93].

2.1.9 Ontology Evaluation

The ever-increasing importance of ontology building makes the evaluation of ontologies vital to the Semantic Web. The evaluation of an ontology is defined by two concepts: validation and

³<http://www.w3.org/Submission/SWRL/>

verification. Ontology validation is concerned with building the correct ontology, while ontology verification is concerned with correctly building an ontology [74]. The validation process ensures that the major requirements of the ontology are satisfied. It evaluates the correctness of the ontology; that is, that the right model of the domain is generated [88]. To validate the correctness of an ontology, a task-based evaluation application can be used with Protocol and RDF Query Language (SPARQL). The Protocol and RDF Query Language (SPARQL) ⁴ can be used to retrieve and work with data stored in RDF format, such as in ontologies.

Ontology verification can be assisted with a web-based tool that scans for major pitfalls. Ontology Pitfall Scanner! (OOPS!) ⁵ is a web tool based on Java Platform, Enterprise Edition (Java EE), Hypertext Markup Language (HTML), javascript Query (jQuery), JavaServer Pages (JSP) and Cascading Style Sheets (CSS). It scans an ontology written in OWL for the main pitfalls that lead to modeling and consistency errors [143]. Then, it provides suggestions based on evaluation results. The categorization and classification options for evaluation with the OOPS! tool are: structural, functional and usability, as well as consistency, completeness and conciseness. Checking on consistency and existing conflicts is a vital task in ontology verification.

A reasoner, which is a software used to derive new facts from existing ontologies, can be used for this purpose. Running a reasoner on an ontology detects inconsistencies and uncertainties and lists ontology errors which can then be fixed by the developer. Pellet ⁶ is an open source, Java-based OWL DL reasoner that can be used as a plugin to Protégé. It executes all the axioms against all data and metadata, checks for logical inconsistencies and reorganizes the class hierarchy, if appropriate. Pellet checks the inconsistencies of an ontology which can lead to incorrect semantic understanding. Pellet is an incremental reasoner; therefore, when an ontology is updated (by adding or removing a component), Pellet uses the previous version with the updated axiom to produce inferred axioms [2].

2.2 Background in Affective States and Their Influences

We argue that psychological theories represent the primary point of ontology design in the domain of human affective states and their influences. These theories form the basis of the existing ontologies that are discussed in Chapter 3. In Section 2.2.1, affective states (emotion, mood and sentiment) are presented. The influences, which are personality, subjective well-being and needs, are introduced in Section 2.2.2. Finally, Section 2.2.3 describes the relationship between affective states and their influences.

⁴ <http://www.w3.org/TR/rdf-sparql-query/>

⁵ <http://oops.linkeddata.es/index.jsp>

⁶ <https://www.w3.org/2001/sw/wiki/Pellet>

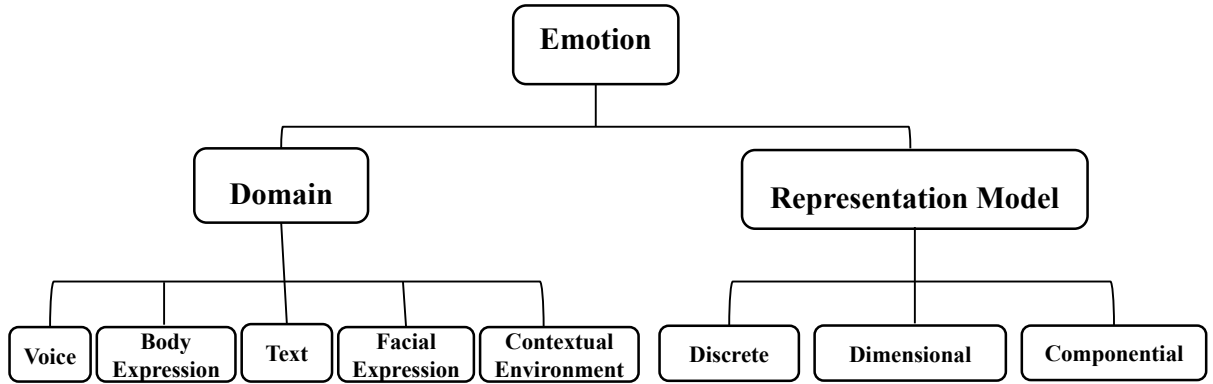


Figure 2.4: The left side shows ways in which humans express their emotions (Domain). The context impacts the expressed emotions. On the right side, psychological models of emotion are shown (Representation Model).

2.2.1 Affective States

Emotion is the result of a person’s exposure to an internal or external stimulus and is expressed by changes in facial expression, gesture, voice or physiological parameters [161]. Emotion plays an important role in a person’s decision-making process. As such, emotion detection is an important step toward the understanding of human beings. Computationally, an emotion can be represented either in a discrete (categorical), dimensional, or componential (appraisal) way [95]. Figure 2.4 provides an overview of the way emotions are expressed and presents representational models.

In the **the discrete model**, emotions are classified by words and grouped into families that share similar characteristics. The most common are called basic emotions (archetypal) and can be found in many cultures. These emotions include happiness, surprise, fear, sadness, anger and disgust [13]. Additionally, neutrality [13], contempt [139], anticipation, trust, and love [139] can be considered. In the work of Izard, contempt, distress, guilt, interest, and shame were added to the basic emotions[97].

Parrott classified emotions in a tree structure that included basic emotions, secondary emotions, and tertiary emotions. Secondary emotions are felt after primary emotions; similarly, tertiary emotions are felt after secondary emotions. For instance, love is a basic emotion while desire is a secondary emotion that often results from love. Furthermore, caring is a tertiary emotion that can be felt after desire [136].

Another discrete emotion classification was proposed by Douglas-Cowie et al., who listed 48

emotion categories and arranged them into 10 groups. They include negative forceful, negative/positive thoughts, caring, positive lively, re-active, agitation, negative not in control, negative passive and positive quiet [52].

Plutchik grouped eight basic emotions in a wheel, placing similar emotions together and opposing others 180 degrees apart. This model, called Plutchik's wheel of emotions, features contrasting pairs: joy versus sadness; anger versus fear; acceptance versus disgust; and surprise versus expectancy. The model also includes advanced emotions made up of combined basic ones. In addition, each emotion in the model represents a basic level of intensity [139].

Furthermore, Drummond used a vocabulary of 10 emotions: happiness, caring, depression, inadequateness, fear, confusion, hurt, anger, loneliness and remorse. These were divided into three categories of strong, medium and light. For example, the emotion of happiness consists of being thrilled in the strong category, cheerful in the medium category and cool in the light category ⁷.

Ortony, Clore and Collins proposed OCC emotion categories, including 22 emotion terms such as relief, pride, shame and gloating [135].

A study done by Fontaine, Scherer, Roesch and Ellsworth (FSRE) used 24 emotion terms (discrete) in their proposed dimensional model [62].

Frijda proposed the use of emotion terms that are related to action tendency [66]. Researchers have also defined other classifications of emotion, including social emotions such as pride, guilt and admiration [4].

In the **the dimensional model** an emotion is represented by a number applied to each dimension. For instance, the Circumplex Model by Russell uses two dimensions, valence and arousal. Valence is correlated with the degree of pleasantness or unpleasantness of an emotion while arousal refers to the amount of physiological change in the person's body [155]. Figure 2.5 shows the Circumplex Model of affect with valence (pleasantness) on the horizontal and arousal (activation) on the vertical axis. As an example, happy is represented by positive valence along with high arousal, whereas relaxed is represented by positive valence along with low arousal (deactivation). In a similar fashion, Whissel models emotion as a 2D space with dimensions of evaluation and activation [183].

Mehrabian created the Pleasure-Arousal-Dominance (PAD) model of emotional states where dominance was added as a third dimension. It is the feeling of being in control of a situation versus the feeling of being controlled [122]. Osgood et al. use the terms evaluation, activity and potency [135], while Cowie et al. use evaluation, activation and power [40]. A fourth dimension, unpredictability, was added by Fontaine [62]. It denotes a person's reaction to a stimulus based on their familiarity with the situation. Watson and Tellegen proposed the dimensions of negative

⁷<http://tomdrummond.com/leading-and-caring-forchildren/emotion-vocabulary/>

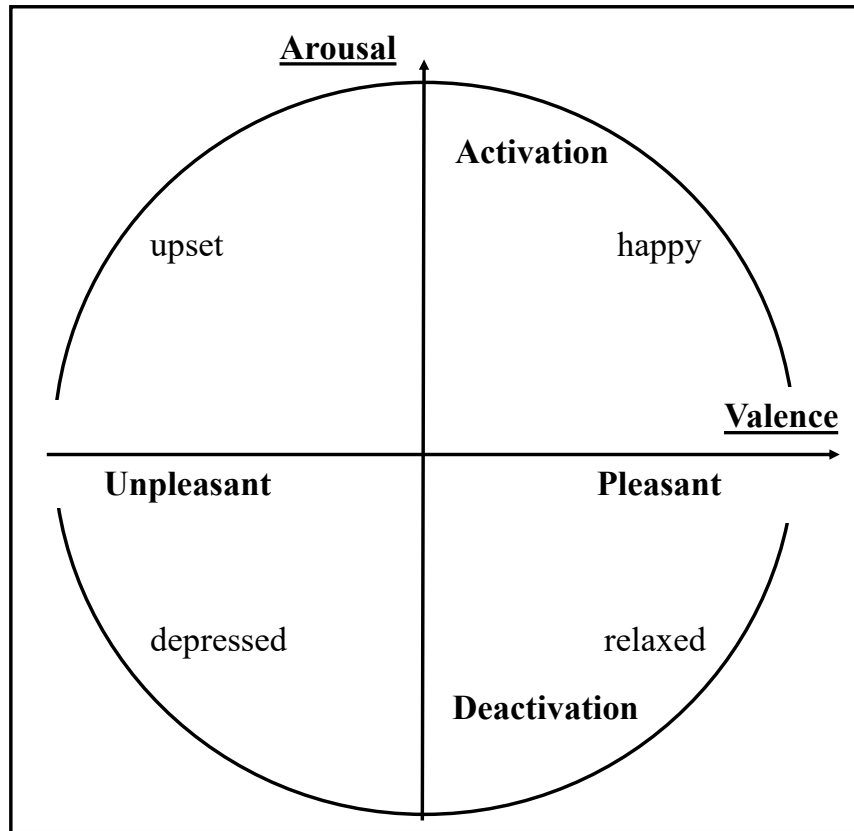


Figure 2.5: A graphical representation of the Circumplex Model of affect. The horizontal axis represents the valence dimension, and the vertical axis represents arousal.

affect (NA) and positive affect (PA) [182] ; in the model of Feidakis et al., intensity, frequency and duration were used as emotion dimensions [58].

The basis of **Componential appraisal models** is the observation that emotions occur in humans as a result of their evaluation of events. This type of model highlights that emotions have a cognitive background. Appraisal theory ties human emotions to the way they interpret events. It states that a person uses fixed criteria to evaluate a situation and to produce suitable emotions. People appraise a situation based on their familiarity with the event (novelty), whether or not it is relevant to their goals, their ability to cope with the consequences of that event (agency), and if it is well-matched to standards and social values (norms) [160].

The OCC (Ortony, Clore, and Collins) appraisal model reasons about agents, beliefs, objects and events. This model is popular in computer science systems that draw conclusions from emotions

[135]. The OCC model defines a finite set that allows for their characterization and also delivers a semi-formal descriptive language of their types. The model classifies 22 emotions into three main categories: consequences of events (e.g., joy and pity), actions of agents (e.g., pride and reproach), and aspects of objects (e.g., love and hate). These three categories are further classified into subgroups. For instance, if an evoked emotion differs depending on whether the consequence of an event is focused on the individual themselves or on others.

Mood is an emotional state that affects the experience and behavior of a person. It has a lower intensity but a longer duration than emotion [161]. Mood affects a person's judgment: people in a happy mood tend to draw optimistic conclusions while people in a bad mood are likely to make pessimistic judgments [110]. Although emotion and mood are both feelings that people experience, there are differences between them. Emotions are caused by a specific situation, they last for a short duration and have a high intensity. By contrast, moods have no clear causes, last longer and have lower intensity [96]. Mood can be represented by using discrete or dimensional models [107].

Sentiment is another human affective state defined by a person's opinion or feeling toward something. Sentiment is expressed with words such as like, dislike, good or bad. For example, people use social media to express their sentiments about products, movies, etc. [94].

2.2.2 The Influences of Affect

Personality is defined as an individual pattern of affect, behavior, cognition and goals over time and space [151]. It reflects a person's attitude and characteristics. The two most popular personality theories are the Myers-Briggs Type Indicator (MBTI) [159], and the Big Five [38]. The MBTI is mainly used in the training world, to perform tasks like determining an appropriate career; the Big Five is the dominant theory used for academic research [21].

As the name implies, the Big Five theory represents personality in five dimensions. An outgoing, energetic person signifies high Extroversion, whereas a friendly and cooperative person demonstrates the Agreeableness trait. Conscientiousness means that someone is responsible, dependable and organized. A sensitive and nervous person has Neurotic traits, while a social, intellectual person has great value in the Openness dimension [120].

In the MBTI, each personality fits into only one of 16 types. These types are based on four features of personality, each one combined with its opposite: Extraversion (E) vs Introversion (I), Sensing (S) vs Intuition (N), Thinking (T) vs Feeling (F), and Judgment (J) vs Perception (P) [159]. Because there are two features within each of the four dimensions, there are 16 possible combinations. Despite the MBTI being a very widespread test of personality, it is noteworthy

that many psychologists do not support it and claim that no significant conclusions can be drawn from it. There is no evidence to show that every individual can be described within 16 categories.

Subjective well-being refers to how people judge and evaluate their lives. The term is a container for diverse types of evaluations. Life satisfaction, for example, is considered a cognitive component because it is based on evaluative beliefs. Positive and negative affect are another component of subjective well-being, reflecting the level of pleasant and unpleasant feelings that people experience in their lives [162].

Human Needs are necessities for the development of an individual's physical and mental growth; they are the underlying layers that trigger emotions and feelings, which later empower and direct human behavior [173]. Need categories are classified and represented by the internal aspect within individuals as well as the external aspects of a particular community, such as social, cultural, economic and political.

In the Self-Determination Theory (SDT) [155], a macro theory focusing on the individual's inner feelings, human needs are categorized into three basic psychological essentials: Autonomy, Competence and Relatedness.

In Human Motivation Theory, Abraham Maslow presents a pyramid of five need categories arranged in hierarchical levels based on their importance to human beings. The five categories, in order of decreasing importance, are survival, security and safety, social, self-esteem, and self-actualization. This model has been updated to adapt two new dimensions under the self-actualization category: cognition and aesthetic needs. This theory also explored self-transcendent needs as the need to help others, which may be added to the top of the pyramid [116].

In the Human Scale Development Model proposed by Max-Neef, the fundamental need categories for individuals and communities are formulated in a universal and interactional structure [118]. The model distinguishes between universal needs and the satisfiers, or strategies involved, to meet those needs. While needs are finite and constant across all human cultures, the satisfiers are changeable over time and differ between societies. The model defines the needs and satisfiers in a matrix with two dimensions. The need dimension in axiological categories consists of: subsistence, protection, affection, understanding, participation, idleness, identity, creation and freedom. The satisfiers in existential categories are represented in the form of being, having, doing and interacting.

2.2.3 The Relationships Between the Affective States and Their Influences

This section explains the connection between the affective states and their influences. It is important to understand that emotion and mood can affect each other. When a person experiences a

frustrating emotion from a specific situation, they may sustain a negative mood as a consequence [31]. Similarly, an individual's personality can impact their life evaluation and behavior. The Big Five personality traits have a major impact on human emotions. For example, when a person with an extroverted personality is offered help by a stranger, they will probably be happy to be offered assistance. Alternatively, if the person has an introverted personality, they may be fearful of the help [54]. Moreover, SWB can be influenced by personality, especially with Extraversion and Neuroticism.

The previous two traits covered the SWB dimensions of life satisfaction and positive/negative affect. Neuroticism is the most significant interpreter of a negative affect and life satisfaction, while extraversion is the most significant interpreter of a positive affect [76]. A human's SWB influences their mood and emotions. When a person makes a positive judgment about their life, they experience positive emotions and are in a good mood. When a person experiences a negative emotion or mood, it is because they feel unhappy about their life expectations [47]. Feelings and emotions are generated by needs and can therefore serve as a guide to identify the state of satisfaction of a person's needs [148]. Thus, a human's needs status can be reported and observed. According to the Nonviolent Communication Theory (NVC), positive and pleasant emotions, such as feeling delighted and thankful, arise when needs are met. On the other hand, negative and unpleasant emotions, such as fear and anger, arise when needs are unmet [153].

There is a relationship between the Big Five personality traits and the PAD emotion model. This relationship is presented as a map between the five traits and the three PAD dimensions. Each trait includes two or more dimensions from the PAD model. Extraversion includes pleasant and dominant characteristics; agreeableness consists of pleasant and submissive characteristics; and conscientiousness relates to pleasure, whereas openness includes pleasant and unarousable characteristics. In addition, neuroticism consists of pleasant, arousable and dominant characteristics. From this mapping, the default mood of a person can be derived. Each trait is given a value between -1 and 1. As a result, the default mood is derived and represented in the PAD model [70, 121].

2.2.4 Recognition Methods for the Affective States and the Influences

In this section, we present some of the existing ways to gather information leading to the recognition of affective states and their influences. There are many ways to obtain data for the identification of emotions, out of which social media and smartphones are popular representatives. For example, emotions can be extracted from social media such as Twitter [101]. Emotions can be automatically detected from geo-tagged posts on Twitter and then visualized on a map [82]. Capturing an individual's speech signals and facial expressions can also aid in the recognition of

their emotions [186]. The use of sensors is another way to measure physical changes and analyze emotions [50]. In addition, a surveillance camera can be used to analyze emotions through facial changes, voice and gestures [17]. There also exist approaches that detect emotion through haptic devices via sense of touch [18].

A person's mood can be inferred from their smartphone communication history and application usage patterns [111], and it can be extracted from social media, such as Twitter [28]. Sentiment can also be detected through social media [7].

There are several methods that can be used to detect the influences of affect. SWB, which corresponds most closely with commonly known feeling of happiness, can be measured by using a smartphone and observing a number of factors. These factors include physical activity, hours of sleep, number of contacts and physical health [129]. Furthermore, people use social media such as Facebook and Twitter to share their opinions, feelings and life expectations [81]. Analyzing messages, watched media, and apps downloaded can help specify an individual's personality [36]. Human needs can also be detected from social media [188]. People reveal their personalities in the way they share knowledge and comment on other topics. A user's personality can be predicted by using public data from Facebook and text from Twitter [72].

2.2.5 Emotion Expression Cues

The experience of emotion incurs a variety of immediate changes in a human being. For example, changes in a person's physiological state may indicate their emotional state [83]; a person's blood pressure increases when they are stressed or angry and decreases when a person is relaxed. Behavioral emotional changes refer to facial expressions, speech and gestures, which can indicate a person's emotions [178], [106],[108]. For instance, the vocabulary someone uses when angry is different from that which is used when they are calm. Another example is when a person is surprised, their mouth opens. Actions and feelings are influenced by a person's emotions. This concept is called subjective experience cues [55]. Emotions can also be expressed via written text. They can be identified by words, such as happy, sad, angry, etc. Moreover, the intensity of emotion in a text can also be analyzed [165].

2.2.6 The Causes of Emotion and Mood

In this section we discuss what causes an emotion or mood to arise. An emotion has a number of possible causes, the most noticeable of which are appraisal, contagion, mood, sentiment and previous emotions. A person's judgment and reaction to a situation is determined by the novelty

of it, in other words, whether or not the situation is new to them. People react to a situation based on their culture, standards and expectations. Moreover, a person's emotions vary based on the significance of the situation. These facts are grouped under the concept of appraisal [42]. In addition, people are often influenced by the emotions of others. For example, when a person is happy but his friend is sad due to a sad event, the happy person may become sad. This notion is called contagion. Moods and sentiments can also control human emotions. If a person is in a positive mood, their emotions are more likely to be positive. Sentiments function in a similar fashion. For instance, interacting with an object to which a sentiment is already attached can arouse certain emotions. Another interesting factor is an individual's previous emotional state, which affects subsequent emotions [32]. Mood also has a variety of causes, the most distinct being emotion. Mood is also contagious.

Chapter 3

Related Work

This chapter presents the existing affective state ontologies and their influences. In Section 3.1, we present the emotion dictionaries that are used later in Section 3.3. In Section 3.2, we discuss general purpose ontologies that were reused by more specific emotion ontologies. Reuse can be a starting point for the creation of a new ontology and can increase domain knowledge [133]. In Section 3.3, existing emotion ontologies are presented. There exist more ontologies that target emotion than there are for mood and other influences. Section 3.4 presents a mood ontology and Section 3.5 introduces a need ontology. Section 3.6 presents the limitation in the existing ontologies. In [1] an overview of existing ontologies is also given.

3.1 Emotion related Lexicons and Language

Emotion dictionaries classify words into emotional dimensions, categories, or both. In addition, they group emotion words into sets of synonyms.

Emotion Markup language (EmotionML)¹ is a general-purpose emotion annotation and representation language that provides a standard emotion representation format. It consists of emotion vocabularies and their features [164]. Figure 3.1 illustrates EmotionML syntax in an annotated text encoded in XML; the emotion category is *afraid* (emotion vocabulary) with intensity 0.4 (emotion feature).

Since the data is annotated in a standard way, the interpretation of the message between systems is the same. EmotionML uses Ekman’s discrete basic emotions and the PAD dimensional model

¹<http://www.w3.org/TR/emotionml/>

```

<sentence id="sent1">
Do I have to go to the dentist?
</sentence>
<emotion
xmlns="http://www.w3.org/2009/10/
emotionml">
category-set="http://www.w3.org/
TR/emotion-voc/xml#everyday
-categories">
<category name="afraid"
value="0.4"/>
<reference role="expressedBy"
uri="#sent1"/>
</emotion>

```

Figure 3.1: EmotionML syntax in an emotional text with annotations encoded in XML.

```

<emotion
category-set="http://www.w3.org/TR/
emotion-voc/xml#everyday
-categories"
expressed-through="face voice">
<category name="satisfaction"/>
</emotion>

```

Figure 3.2: EmotionML syntax for an emotion that was detected from face and voice.

to represent emotions and their features. The language can be applied in different contexts, such as data annotation and emotion recognition. The annotation can be applied to text, static images, speech recordings and video. Figure 3.2 demonstrates a case where an emotion is recognized by face and voice.

WordNet² is an online lexicon for the English language and it distributed into five categories: nouns, verbs, adjectives, adverbs and function words. It clusters words together based on their meanings and defines semantic relations between words, as well as grouping them into sets of synonyms called synsets. WordNet currently contains 155,287 words, organized into 117,659 synsets [123].

²<https://wordnet.princeton.edu/>

SentiWordNet ³ is an enhanced lexical resource for supporting sentiment classification and opinion-mining applications. It assigns three scores to each synset in WordNet: positive, negative and neutral. This annotation indicates how positive, negative and neutral the terms in each synset are. For example, a sentence with a positive word, such as happy, will have the following scores: 1 (positive), 0 (negative), 0 (neutral) [16].

To include concepts of affect, **WordNet-Affect** ⁴ was developed as an extension that labels synsets with emotion, mood and behavior. WordNet-Affect creates an additional hierarchy in WordNet with emotion labeling. The hierarchy of WordNet-Affect categorizes emotion words into classes such as positive, negative and neutral [168].

MultiWordNet ⁵ is an extension of WordNet with a multilingual lexical database. It is available in Italian, Spanish, Portuguese, Hebrew, Romanian and Latin. The important relationship between words is called synonymy. A group of synonyms identifies a concept [138].

SenticNet 3 ⁶ is a concept-level opinion lexicon for sentiment analysis. It includes polarity for words and multi-word expressions. The polarity can be a number in the range between -1 and 1, or it can be a flag (positive or negative). SenticNet 3 contains 30,000 common and common-sense concepts. It is different from other sentiment analysis resources such as WordNet-Affect because it associates semantics and sentics with common and common-sense knowledge. Common-sense knowledge can help to determine the polarity of a concept in a multi-word expression sentence. This improves subsequent text-based sentiment analysis [33].

HowNet ⁷ is an online bilingual English and Chinese ontology that describes the semantic relations between concepts and their attributes. A semantic relation can be expressed as synonym, antonym, etc. The top level classification in HowNet includes entity, event, attribute and attribute value. HowNet uses 80,000 words and phrases to build the ontology. The semantic relation between concepts is language-dependent. The nature of Chinese language is unlike English, so the semantic relation between Chinese concepts is different from English concepts [51].

NRC Word-Emotion Association Lexicon ⁸ The National Research Council of Canada's (NRC) emotion lexicon is a list of English words and their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy and disgust) and two sentiments (negative and positive). Moreover, NRC Emotion is available in other languages such as Arabic, French, Japanese, Spanish, etc [125].

³<http://sentiwordnet.isti.cnr.it/>

⁴<https://www.gsi.dit.upm.es/ontologies/wnaffect/>

⁵<http://multiwordnet.fbk.eu/english/home.php>

⁶<http://sentic.net/>

⁷http://www.keenage.com/html/e_index.html

⁸<http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm>

The Harvard General Inquirer ⁹ is a lexicon attaching syntactic, semantic to part-of-speech tagged words [167].

MPQA Subjectivity lexicon ¹⁰ labeled the word with information about its polarity (positive, neutral or negative), as well as the intensity of the polarity (weak or strong) [184].

AFINN ¹¹ is a dictionary that has a list of English words rated for valence with an integer between -5, +5 and zero for neutral [131].

SentiStrength ¹² is a dictionary that has a list of English words especially for short text, rated with an integer between -5, +5, and zero for neutral [176].

In addition, we used the Oxford English Dictionary ¹³ to extend the list of synonyms.

In the field of the Semantic Web, there are many lexicons available that represent data in different formats. For example, the amount of speech parts can differ between lexicons. Moreover, it is difficult to link them with existing ontologies. The **Lexicon Model for Ontologies (LEMON)** [119] supports the sharing of terminological and lexicon resources on the Semantic Web, and connects them with existing ontologies. LEMON was built based on semantics by reference; the principle consists of two layers, lexical and semantic. The lexical layer describes the morphology and syntax of a word, and considers the suffix and the prefix. Semantic layers describe the meaning of a word and the core classes in the ontology allow the definition of a lexicon with a specific language and topic. Compared to WordNet, LEMON is richer in word format and representation.

3.2 Re-Used ontologies

This section introduces general ontologies that are being reused for the creation of existing emotion ontologies discussed in Section 3.3.

An ontology can be reused because it models an upper ontology (general) that can be extended and fit into many domains, such as CONtext ONtology (CONON) and Friend Of A Friend (FOAF). Moreover, an ontology can be reused because it represents a model for a specific domain, such as Provenance Ontology.

CONtext ONtology (CONON) [80] is used for modeling context in pervasive computing environments. The purpose of CONON is reasoning and representation in context-aware applications.

⁹<http://www.wjh.harvard.edu/inquirer/>

¹⁰ http://mpqa.cs.pitt.edu/lexicons/subj_lexicon/

¹¹ http://www2.imm.dtu.dk/pubdb/views/publication_details.php?id=6010

¹² <http://sentistrength.wlv.ac.uk/>

¹³ <https://en.oxforddictionaries.com/>

CONON defines an upper ontology (general) that represents context and situations, and can be extended by adding a domain-specific ontology. For example, CONON contains classes about a person, their location (indoor space and outdoor space) and their activity. These classes describe the contextual environment that surrounds the person. In addition, the ontology includes a class for computing devices, such as applications and networks.

Friend Of A Friend (FOAF)¹⁴ is an ontology used to describe a person, their activities and their relations to other people. It consists of classes that represent a person (first name, family name) and their gender, age, education, organization, homepage, culture, information about organizational project(s) they are involved in, etc. It also includes an MBTI personality classification that allows a user to find people of European culture, or people who know a certain person in a machine-readable way. Figure 3.3 shows a part of the FOAF ontology that contains a person's name, email address, homepage and another person they know.

The **Provenance Ontology** [127] was built to establish trust in published scientific content. The three classes *Agent*, *Activities* and *Entities* provide the starting point. Agents could be people, an organization, or software that produces activity on the data (entity). The activity can be data-processing, such as transforming data into a different format. By using the Provenance Ontology, the history and the life cycle of a document can be obtained. The ontology also allows systems in its domain to exchange data due to uniform terminology.

3.3 Emotion Ontologies

Daily human communication involves many emotions [13] that can be expressed through text, facial expression, voice and body language. Emotion can also be influenced by the contextual environment. A person can express the same emotion in different situations (contexts), but with varying intensity. Emotion ontologies can also describe general concepts. We categorize existing ones into the five domains, as they are shown in Figure 2.4.

3.3.1 Text Domain

A lot of work has been put into building ontologies that analyze and detect emotion from text. People express their emotions with words both formally and informally. For instance, text in social media has unique characteristics: users often employ slang terms and abbreviations, as well as expressing their emotions via emoticons.

¹⁴<http://www.foaf-project.org/>

Table 3.1: Summary of emotion ontologies in the text domain. In addition to the reference, the names of the ontologies are listed if available.

Ontology Name/Prefix	Goal	Emotion Model	Ontology Re-Use	Lexicon/Language
Emotions Ontology [157]	Analyze unstructured data	Discrete		
Emotive Ontology [172]	Detect and analyze emotion in informal text from social media	Discrete		WordNet, Dictionary.com, Thesaurus.com, Oxford Dictionary, Merriam-Webster Dictionary
[10]	Give the student the right feedback in e-learning	Discrete		
Ontology of Emotions and Feelings [117]	Automatically annotate emotion in text	Discrete		
[145]	Analyze emotion in text	Discrete and Dimensional		EmotionML
[100]	Define emotion words and their intensity	Discrete and Dimensional		Japanese Emotion Expression Dictionary, EmotionML
[187]	Analyze emotion in text	Discrete		HowNet
Onyx [158]	Annotate emotion in user generated content	Discrete and Dimensional	Lemon, Provenance Ontology	EmotionML, WorNet-Affect
SO [147]	Represent the structure and the semantics of emoticons	Discrete		
VSO [30]	Detect sentiment from visual content	Discrete		SentiWordNet, SentiStrength

```

@prefix foaf:
<http://xmlns.com/foaf/0.1/>.
@prefix rdfs:
<http://www.w3.org/2000/01/rdf-
schema#>.
<http://njh.me/#JW>
a foaf:Person;
foaf:name "Jimmy Wales ";
foaf:mbox
<mailto:jwales@bomis.com>.
foaf:homepage
<http://www.jimmywales.com/>;
foaf:nick "Jimbo ";
foaf:depiction
<http://www.jimmywales.com/aus_
img_small.jpg>;
foaf:interest
<http://www.wikimedia.org>;
foaf:knows [
a foaf:Person;
foaf:name "Angela Beesley"
] .
<http://www.wikimedia.org>
rdfs:label "Wikipedia" .

```

Figure 3.3: Example from FOAF Ontology.

Many ontologies were built to analyze text in social media. Some of the ontologies in the text domain were created for a particular purpose, focusing on international languages like English, Chinese, Japanese, French and Italian. Table 3.1 summarizes emotion ontologies in the text domain. The table contains columns displaying the ontology name or prefix, the goal, the emotion model that is used, other ontologies that were re-used, and the lexicons that provided the terminology. The used emotion models can be discrete, dimensional, or based on the OCC model. It should be noted that some ontologies were built "from scratch" and are not based on existing lexicons. This leads to some cells being empty in Table 3.1.

A system was built to analyze unstructured, informal text within posts about electronic products; this was done to understand online consumer behavior in the market [157]. The aim of the sys-

tem was text-mining in social media, so the *Emotions Ontology* was created in order to analyze consumer behavior. One of the main classes in the ontology is *Sentiment*, with two subclasses *Happiness* and *sadness*. For example, beneath happiness exist the subclasses enjoy, fun, eager and smiling; beneath sadness is dislike, disappointed, bad and worst. Additionally, the ontology contains classes about products such as computer and household. The system is comprised of four modules: ontology management module that contains the created ontology, a user query processing module, an information foundation module and a query analysis engine module. The ontology models the product with associated emotions that are based on social media posts. A user can then operate the system to make a query about the product with a specific emotion.

The *Emotive Ontology* [172] was built to detect and analyze emotion in informal text from social media. This approach involves detecting a range of eight high-level emotions: anger, confusion, disgust, fear, happiness, sadness, shame and surprise. Each emotion in the ontology is named according to prior work (Izard, Ekman, Plutchik, Drummond); also included are commonly encountered emotions within Twitter messages. The Emotive Ontology is also capable of expressing the intensity of emotions. During its creation, many dictionaries and word datasets were examined, such as WordNet, Dictionary.com, Thesaurus.com, the Oxford English online dictionary and the Merriam-Webster online dictionary. Since the goal of the ontology is to detect emotion from informal slang text, websites that contain slang expressions were also examined. Examples are the Leicestershire Slang Page, the Dictionary of Slang, and the Online Slang Dictionary. To make sure the emotion set covered was as large as possible, existing emotional lexicons were integrated into the Emotive Ontology. Natural Language Processing (NLP) and some speech tagging were used as pre-processing steps for emotion detection. The ontology was tested and evaluated on a dataset taken from Twitter.

An ontology that helps to give students appropriate feedback in e-learning sessions was proposed by Arguedas et al. [10]. It is divided into the two main classes, Emotion Awareness and Affective Feedback. In the former emotion is analyzed and in the latter, the appropriate feedback given from teacher to student is determined. The emotion awareness class includes different types of emotions in a categorical model, moods (bored, concentrated, motivated, unsafe) and behaviors that students experience in e-learning environments. Emotion is detected during collaborative virtual learning processes, including textual conversations, debates and wikis.

In [117] the *Ontology of Emotions and Feelings* automatically annotates emotion in texts and determines their intensity. This French ontology classifies 950 words (600 are verbs and 350 are nouns) into 38 semantic classes according to their meanings. Words in the lexicon are emotionally labeled as positive, negative or neutral. NaviTexte, a software designed for text navigation, was used to apply this ontology. It understands and applies knowledge to a specific text [39]. The goal of the ontology is to automatically annotate emotions and navigate through text.

An ontology of emotion objects is introduced in [145]. Emotion objects are collected from a large, Japanese blog corpus. An emotive expression lexicon for Japanese language is used to distinguish emotion words. The ontology was created using an EmotionML annotation scheme that was modified to meet the needs of the Japanese language. The ontology classes represent emotion, according to Nakamura's classification, which is "a collection of over two thousand expressions describing emotional states collected manually from a wide range of literature" [144]. Here, emotion is represented in a dimensional model. The ontology also contains classes for number of characters, parts of speech and semantic categories. In the latter class, emotion objects are categorized into groups, such as human activities and abstract objects.

To define Japanese emotion words and their intensity, an emotion ontology specific to the nationality was proposed [100]. Emotion words were taken from websites such as Twitter. Calculation of intensity is based on the number of times an emotion word appears in a document. The words are categorized into ten emotions: joy, anger, sadness, fear, shame, like, disgust, exciting, comforted and surprise. The authors adapted their ontology into other emotion classifications, positive, negative and neutral; the Pleasure-Arousal-Dominance theory was adapted as well. Both OWL and EmotionML were used to describe the ontology. One of the proposed applications for this is as a character generator. When the system receives voice inputs, the audio is then translated into text and analyzed by the emotion ontology. The output is a character with facial animations.

To analyze Chinese text, a Chinese emotion ontology was created [187]. It was created semi-automatically using HowNet and contains 113 emotion categories. It was created by first extracting affective events from the dictionary, then manually assigning emotions to the semantic role of events, producing the Emotion Prediction Hierarchy. Finally, the latter hierarchy is transformed into the emotion ontology. This step involves assigning verbs extracted from the dictionary to the Emotion Prediction Hierarchy.

The *Onyx Ontology* [158] offers a comprehensive set of tools for any kind of emotion analysis, even at an advanced level. It reuses the Provenance Ontology and the LEMON model. In the Provenance Ontology, the activity is emotion analysis, which means turning plain data into semantic emotion information. The Onyx ontology thus has a class called *Emotion Analysis* that is responsible for representing the information source (for example, a website), the algorithm used, as well as the emotion model. The *Emotion Set* class contains information about a group of emotions found in a text, including the person expressing the emotion, the domain, information about the original text and the sentences that contain the emotion. The *Emotion* class of the ontology contains information about the emotion model, appraisal, action tendency and emotion intensity. To support the annotation process, WorNet-Affect and EmotionML were used. Two different testing scenarios were created in order to evaluate the ontology; the first is to make queries against the ontology, and the second is to translate EmotionML resources to Onyx and vice versa.

Users of social media express their emotions using emoticons. The *Smiley Ontology* (SO) represents the structure and semantic meaning of emoticons [147], which allows an application to understand and utilize them. Moreover, it allows applications to exchange emoticons with the correct interpretation. The ontology design is based on Smiley Layer Cake ¹⁵ and the model consists of three layers. The bottom layer deals with the message between the sender and the receiver (Underlying Emotion), while the second layer is the (structure) of the emoticon, representing the emoticons contained in the message, such as text, face or object. The top layer (Visual Appearance) describes the appearance of the emoticon, such as its colour and whether it is animated or not. The core class of the Smiley Ontology is Emoticon, which can be visually represented as a sequence of characters, a picture, or both. Each system has its own set of images. This ontology has a class named Emoticon System that contains all possible pictures for emoticons generated from a social software tool.

The *Visual Sentiment Ontology* (VSO) [30] was proposed to detect sentiment from visual content. Its psychological foundation is Plutchik's wheel of emotion. The initial step in building the ontology was to retrieve images from Flickr and videos from YouTube and then to analyse the tags associated with these images and videos. Thus, the top 100 tags for various emotions were obtained. For each tag, the sentiment value was computed according to the two linguistic models SentiWordNet and SentiStrength [177]. Due to the use of linguistic models on image tags, we decided to categorize the VSO into the text domain. The assigned sentiment value for each emotion word ranges from -1 (negative) to +1 (positive), and the words obtained from the tags were classified into nouns and adjectives. From the collected data, Adjective Noun Pairs (ANP) like "misty night" or "colourful clouds" were obtained. Furthermore, the VSO contains more than 3,000 ANP; the top level of it shows the relationship between the emotions, ANP and sentiment values. One application of VSO is the prediction of a sentiment expressed in a Twitter image.

3.3.2 Facial Expression Domain

It has been shown that emotional facial expressions make up 55% of our communication [13]. Emotion is expressed in humans through facial movement. For example, when a person is surprised, they open their mouth and raise their eyebrows. Table 3.2 summarizes emotion ontologies in the facial expressions domain.

An emotion ontology was created to support the modeling of emotional, facial animation expression in virtual humans; this was done within Moving Picture Experts Group (MPEG-4) [69]. Human actions were translated into a virtual world with avatars by using an ontology. A virtual world (environment) is a computer graphic-based environment that generates the impression that

¹⁵<http://www.slideshare.net/milstan/beyond-social-semantic-web>

Table 3.2: Summary of emotion ontologies in the facial expression domain.

Ontology Name/Prefix	Goal	Emotion Model	Ontology Re-Use	Lexicon/Language
[69]	Model emotional facial expressions in virtual environments	Discrete and Dimensional		
[90]	Represent non-verbal behavior in virtual environments	Discrete		
OLA [57]	Predict students' emotions during e-learning	OCC		

the user is in a place different than their actual location [56]. The ontology allows for storing, indexing and retrieving the correct information about facial animation for a given emotion. The ontology defines the relationship between facial animation concepts as standardized in MPEG-4 and emotions. It contains the classes *Face*, *Face Animation*, *Face Expression*, *Emotion* and *Emotion Model* (Ekman and Plutchik). In addition, there is a class for the parameters of facial animations. To use the ontology and extract the correct information for a specific emotion, the Racer Query Language interface for OWL was used [19]. This query language is close to natural language; for example, we can query using following question: What is the facial animation that expresses a depressed emotion?

Another emotion ontology was proposed within a framework called Nonverbal Toolkit, used for the cooperation of heterogeneous modules that gather, analyze and present non-verbal communication cues [90]. The aim of this framework is to gather nonverbal behavior in the real world and represent it in a virtual environment, such as with an avatar in second life ¹⁶. To ease communication and the exchange between the modules, an ontology was developed. The ontology defines shared vocabulary that can be understood and used by all modules. It represents emotion by using a categorical approach (Ekman Model), as well as complex emotions, which are a combination of two or more simple emotions. For a good representation of the non-verbal communication cue level in the virtual environment, emotion intensity is also specified. Moreover, the affective states are partially derived from personality traits. Human personality affects the expressed emotion and its intensity.

In the e-learning domain, the *Ontology for Predicting Students Learners' Affect* (OLA) [57] was

¹⁶<http://secondlife.com>

introduced based on the OCC model of emotions. An interactive application was designed to estimate student emotion when interacting with a quiz about Java programming. The application monitors and records student action when answering questions and saves them in the student's log file. When a student does not answer a question correctly, the event status is confirmed and appreciation is set to disliking. Alternatively, when the student answers a question correctly, appraisal become desirable. So, the log file data input allows the ontology to compute the OCC model variables that predict student emotion, using ontology inference. Students may express different emotions while answering a single question, therefore, student emotions were studied in three different situations: When they saw the question for the first time, when they chose the answer, and when the correct answer was displayed.

3.3.3 Voice Domain

Emotion can be detected from voice by analyzing its change in tone, volume, rate, pitch, and pauses between words [63]. In voice emotion extraction, the EmoSpeech system was built to convert unmarked input text to emotional voice. The developed emotion ontology (OntoEmotion) is organized in a taxonomy that covers a range of the basic emotions to the most specific emotional categories [63]. OntoEmotion is presented in English and Spanish and the emotion class in the ontology uses the categorical model. The ontology represents the specific words each language uses to denote emotion; its class is named *Word*. To categorize words in English and Spanish, the class *Word* has two subclasses named *English Word* and *Spanish Word*. Another class in the ontology defines emotion synonyms, while emotion concepts are linked to the three emotional dimensions of Evaluation, Activation and Power. The EmoSpeech system uses EmoTag, which is a tool for automated markup of texts with emotional labels. These values are the input for the ontology, which then classifies it into an emotional concept. Next, the text is read aloud with the emotion assigned by EmoTag. For instance, EmoTag was applied on fairy tale stories in English and Spanish to annotate emotions [64]. Another application was designed to extract rich emotional semantics of tagged Italian artistic resources through an ontology method [20]. To select the tags that contain emotional content, several Semantic Web and natural language processing tools were incorporated, such as multilingual (MultiWordNet) and affective lexicons (WordNet-Affect, and SentiWordNet). The software uses OntoEmotion because its taxonomic structure reflects psychological models of emotions and is implemented by using Semantic Web technologies. However, the ontology was enhanced by adding a new subclass named *Italian Word* to the root concept *Word*.

Table 3.5 summarizes individual ontologies from the following domains: Emotion Voice Domain (OntoEmotion), Emotion Body Expression Domain, mood (COMUS) and need (FHN). Since

Table 3.3: Summary of emotion ontologies in the contextual environment domain

Ontology Name/Prefix	Goal	Emotion Model	Ontology Re-Use	Lexicon/Language
[22]	Represent the affective states for context aware applications	Discrete	CONON	
BIO_EMOTION [189]	Recognize emotion based on the user's biomedical factors and environment	Discrete and Dimensional		

there is only a small number of ontologies in these domains, we decided to create a table for miscellaneous domains.

3.3.4 Body Expressions Domain

Gestures and expressions of the human body can convey emotion. In [68] an ontology of body expressions that represent gestures in virtual humans within MPEG-4 is presented. Animations are annotated with emotional information by using Whissel's wheel of emotion. Because of the complexity of bodily expression, gestures were associated with emotions. In the ontology, seven gestures were considered; for example, hand clapping is associated with joy and excitement. To use the ontology, a query with natural language was used.

3.3.5 Contextual Environment Domain

Analyzing emotions within a given context provides insight to the relationship between an emotion and its cause. Table 3.3 summarizes emotion ontologies in the contextual environment domain.

An ontology was generated to represent the affective states in context-aware applications in [22]. It expresses the relationship between affective states and other contextual elements such as time and location. It expresses the relationship between affective states and other contextual elements, such as time and location. The ontology is built on the existing ontology, CONON, and its Emotion class (state) uses Ekman's basic emotions. In addition, the class named Secondary contains emotion that is related to the targeted scenario. The ontology was applied to an art museum visit,

where a person moves from one room to another while their emotions are monitored. The secondary emotions were found to be relaxed and stressed. The ontology represents the most powerful emotion (dominant). Object properties are used to express the relation between emotions and context elements. The ontology in [105] was built based on the previous ontology [22]. However, emotion was defined by three possible data type properties: positive, negative and neutral.

The BIO_EMOTION ontology recognizes emotion based on the user's electroencephalographic (EEG) and bio-signal features, as well as the situation and environmental factors [189]. It also supports reasoning about the user's emotional state. The focus of the ontology is mapping between low-level biometric features and high-level human emotion. Inference rules are defined by using corresponding relationships between EEG and emotion. BIO_EMOTION consists of 84 classes and 38 properties. The Emotion class defines user affective states. Emotions are represented by Ekman's discrete model and the dimensional circumplex model. User context is represented by the Situation class through location, time and event, and demographic information like name, age, and gender is integrated into the ontology. Additionally, a class to represent bio signals was provided. The machine learning software WEKA was used to generate IF-THEN statements in the reasoning process¹⁷. To evaluate the ontology, the DEAP dataset was utilized, which is a database for emotion analysis that employing physiological signals [102].

3.3.6 General Domain

General ontologies, also called upper level ontologies, have been proposed to recognize emotion. They define general concepts that are common in a domain. Such ontologies can be extended according to the developer's purpose by defining domain-specific classes, or they can be linked to an existing domain-specific ontology. Table 3.4 summarizes emotion ontologies in the general domain.

A high-level ontology named the *Human Emotions Ontology* (HEO) was developed in order to annotate emotion in multimedia data [78]. Its main class is *Emotion*, which is expressed in dimensional and categorical models. An emotion has intensity, appraisals and action tendencies; it can also be expressed through face, text, voice and gesture. Additionally, the ontology contains classes for multimedia content and the annotator of the media. The Annotator class has two subclasses: Human or Machine (automatically annotated). Since the emotion is expressed by a person, HEO reuses the Friend Of A Friend (FOAF) ontology. A subclass Observed Person of class Person was created in FOAF and connected to the Emotion class of HEO. Moreover, some object properties were added in FOAF that are relevant to emotion, such as age, culture, language and education.

¹⁷<http://www.cs.waikato.ac.nz/ml/weka/>

Table 3.4: Summary of emotion ontologies in the general domain.

Ontology Name/Prefix	Goal	Emotion Model	Ontology Re-Use	Lexicon/Language
HEO [78]	Annotate emotion in multimedia data	Discrete and Dimensional	FOAF	
[134]	Describe emotional cues	Discrete and Dimensional		
SHEO [11]	Identify complex emotions in text	Discrete and Dimensional	HEO	

The *Semantic Human Emotion Ontology* (SHEO) [11] was built based on HEO to identify complex emotions composed of two or more simple ones. For instance, the complex emotion of contempt is a combination of the two basic emotions anger and disgust. Software was designed to use the ontology for analyzing simple and complex emotions in text as well as in images.

In the general context, the *Ontology of Emotional Cues* was proposed to describe emotional cues at different levels of abstraction [134]. Concepts are gathered into three modules to detect emotion, which is represented by a categorical and a dimensional model. An emotional cue can be simple or complex and this is represented in the emotional cue module. A simple cue can be expressed through facial expressions, gesture and speech while complex emotional cues are a combination of two or more simple cues. The media module describes the properties of the emotional cues.

3.4 Mood Ontologies

Mood can affect a person's daily life choices. Building ontologies that can match a person's mood with their desires allows for greater satisfaction. People often choose the music they listen to based on their current mood.

A recommendation-based music system was built with the *Context-Based Music Recommendation Ontology* (COMUS) to retrieve music in a semantic way [124]. The ontology reasons about the user's mood, situation and preferences and it consists of classes concerning the *Person*, their *Mood* and the *Music*. The COMUS Ontology is connected to many ontologies such as FOAF. Some classes in COMUS, such as the Person class that includes personal information, are similar to the FOAF ontology. The Person class defines general personal properties such as name, age, gender and hobby. Additionally, the ontology represents user contexts event, time and location. The Mood class use a discrete model. Each mood class has a sub-class of mood similarity;

Table 3.5: Summary of individual ontologies that do not fit into the domains of the other tables

Ontology Name/Prefix	Goal	Model	Domain
OntoEmotion [63]	Convert un-marked input text to emotional voice	Discrete and Dimensional	Emotion Voice Domain
[68]	Represents body gestures in a virtual environment	Dimensional	Emotion Body Expression Domain
COMUS [124]	Retrieve music in a semantic way	Discrete	Mood
FHN [53]	Express the relationship between various needs and their satisfiers	Manfred Neef	Max-Need

for example, aggressive is similar to hostile, angry, etc. The other classes are domain-specific and related to music. Users can ask the music recommender system to find songs based on their mood. The system then delivers the appropriate music to them with the help of the ontology.

3.5 Need Ontologies

Understanding and conceptualizing human needs helps to achieve human satisfaction. Building ontologies that define human needs through vocabulary and relationships allow systems to be built that can automatically interpret and serve those needs. The Fundamental Human Needs Ontology (FHN) was introduced to express the relationship between various needs and their satisfiers [53]. The ontology is based on the needs model by Max-Neef. It represents the Agent and his or her Role, their Needs and Satisfiers. A person can play different roles, and each role requires different satisfiers. For example, when a person is at home their needs are satisfied differently from when they are at work.

3.6 Conclusion

There are strong relations between human affective states and their influences. Indeed, human behavior is impacted by emotion, mood, personality, needs and subjective well-being (SWB). Affective states are the experiences, or the feelings, that a person can have. Affective states can have influences that might impact the type of feeling or experience in question. Emotion, mood and sentiment are human affective states, while personality, needs and subjective well-being are influences on those affective states. Therefore, it is valuable to represent the human affective states and their influence in one ontology.

After surveying and analyzing existing ontologies, we realized that great effort has been made to build those that detect and annotate emotions, whereas there are only several that target mood and human influences. We believe that investigating ontologies for mood, sentiments, needs and personality, as has been done for emotion, is an interesting and important avenue for future research.

Subjective well-being resembles human life satisfaction, which in turn leads to positive emotion and good mood. It is thus a significant influence factor on human affective states. After exploring existing ontologies, to the best of our knowledge we did not find any regarding subjective well-being.

Furthermore, the Big Five personality trait theory is fairly well known in academic research; therefore, it is important to represent it in an ontological format. We believe that creating ontologies for subjective well-being and the Big Five personality traits are also interesting future fields of research.

After analyzing existing ontologies, we recognized the need to develop HASIO. It represents the knowledge that is necessary to model affective states and their influences in a computerized format. It describes the human affective states (Emotion, Mood and Sentiment) and their influences (Personality, Need, Subjective well-being), as well as conceptualizing their models and recognition methods. HASIO also represents the relationships between affective states and the factors that influence them. HASIO emphasizes the use of well-known psychological theories in developing an ontology in human affective states and their influences domain.

Chapter 4

Human Affective States and their Influences Ontology (HASIO)

In this chapter we discuss the actual development and conceptualization of the HASIO. Human behavior is based on emotion, mood, sentiment, personality, needs and subjective well-being (SWB) [112], [46], [137]. Emotion, mood, and Sentiment are the human affective states, whereas personality, needs, and SWB are influences on those states. When humans attempt to understand and discuss these states with one another, it is not uncommon for misunderstandings to arise, so it creates further challenges for inter-computer communication. This is particularly significant if the applications come from different domains and are not intended to communicate with one another in the first place [181]. Representing the five human domains (emotion, mood, personality, etc.) in a semantic way is one means of solving this problem. Representing the affective states and their influences in an ontology allows for clear communication between people and between machines in this domain [174]. Moreover, it enables the creation of an effective application that automatically detects, predicts, analyzes or simulates human domains [152].

The Human Affective States and their Influences Ontology (**HASIO**) has been developed in the OWL language. It provides knowledge about human affective states and their influences as well as a common vocabulary in a machine-accessible or readable format.

In this chapter we discuss the development and conceptualization of HASIO. The development of an ontology can be accomplished using a number of different methods, depending on its requirements. There is no standard or uniquely correct way to build an ontology; however, there should be a guide to provide support, starting with information-gathering and working toward development.

In [60] Fernandez et al. present an ontology methodology called Methontology. It assists users

in the building process and contains the entire life cycle of the ontology in the development process. Development starts with the preliminary stage, which identifies the need to build an ontology and finishes with the completed product, the evaluated ontology. These steps or stages should be followed sequentially, and in an iterative manner if necessary. Methontology covers groups of activities and states.

HASIO¹ was engineered and developed according to Methontology. In Section 4.1 we specify the components, techniques and aspects of the methodology used to develop HASIO. In Section 4.2 we present HASIO's class-subclass structure. In Section 4.3 we provide HASIO's object properties. Furthermore, in Section 4.4 we present HASIO SWRL. In Section 4.5 we present HASIO modularization. Finally, in Section 4.6 we highlight the HASIO engineering process.

4.1 Methontology

Methontology consider a mature methodology. Methontology is considered a mature methodology that supports the entire ontology life cycle. It is a framework that supports building ontologies either from scratch, by reusing other ontologies as they are, or by reengineering them. Its proposal was based on IEEE standard for software development [37]. Moreover, it allows going to previous states if needed. Indeed, there is no specific consensus on which methodology is best for ontology building however, the purpose or need to build an ontology can be the starting point in selecting the appropriate methodology. The key strength of Methontology is the detailed description of included activities [59], [67].

The first step of the Methontology is *Specification*. This step requires a written document in a natural language that contains ontology information (metadata). Second the *Knowledge Acquisition* phase, which involves knowing the information and resources required for development. *Conceptualization* is the third step, requiring the construction of the ontology's abstract view. Fourth is *Integration*. In this stage, the developers consider reusing and/or reengineering existing ontologies. The last step is the *Implementation* phase where developers use an ontology environment based on the previous steps. Specification, conceptualization, integration, and implementation are *states* of ontology development that should be pursued in this order and in an iterative manner, while knowledge acquisition, documentation, and evaluation are *activities* that are done simultaneously with the states. Figure 4.1 summarizes the ontology building states and activities.

¹HASIO can be downloaded under the link : <https://github.com/rana-othman/Huam-Affective-States-and-their-influences-Ontology-HASIO>

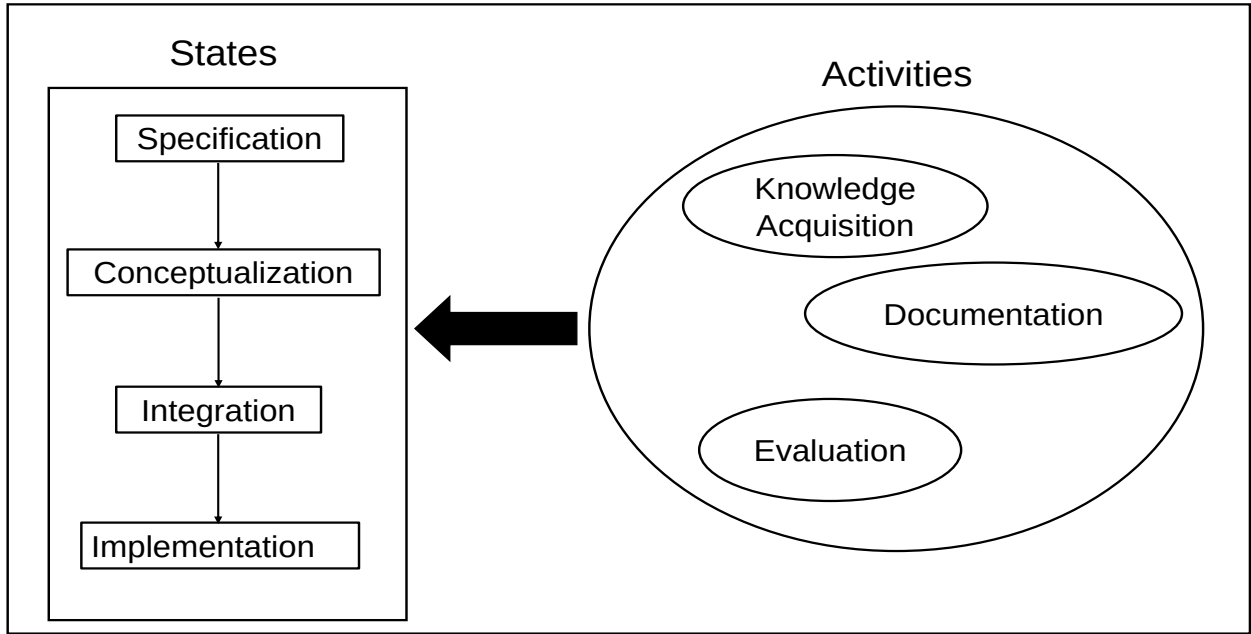


Figure 4.1: Ontology building states and activities.

4.1.1 HASIO Specifications

We followed the *Ontology Metadata Vocabulary* (OMV) to produce HASIO specification². OMV specifies the ontology features in human and machine-readable formats. Ontology metadata allows developers to use existing ontologies; as a result, the process of ontology knowledge-sharing and reuse is facilitated. Thus, ontology metadata makes understanding and reusing existing ontologies more efficient and effective [85]. Figure 4.2 shows the HASIO metadata, which covers the following fields: name, location, created by, language, syntax, type, formality level, domain and purpose of the ontology, engineering methodology, and task. We took advantage of OWL's features to develop HASIO, such as class disjoint, existential restriction, inverse Property and Asymmetric Property.

The **NeOn Methodology** was chosen for the HASIO engineering methodology. It provides tangible plans for the reuse and reengineering of knowledge sources and it classifies various, flexible scenarios for building ontology networks. Developers can choose scenarios that meet the ontology requirements and goals [171]. HASIO follows select scenarios offered by NeOn, including

²<http://mayor2.dia.fi.upm.es/oeg-upm/files/omv/OMV.owl>

HASIO Specification Document

Ontology Name: Human Affective States and their Influences Ontology (HASIO)
Location: Canada, Ottawa, University of Ottawa
Created By: Rana Abaalkhail , rabaa006@uottawa.ca
Ontology Language: OWL
Ontology Engineering Tool: Protégé
Ontology Syntax: rdf xml Syntax
Ontology Type: Domain Ontology
Ontology Formality Level: Define Terms with Formal Semantics
Ontology Domain and Purpose: The ontology describes the human affective states (Emotion, Mood, Sentiment) and their influences (Personality, Need, Subjective well-being). It conceptualizes their models and recognition methods. It also represents the relationships between affect and influencing factors.

Ontology Engineering Methodology:
Based on NeOn Methodology; HASIO follows the following scenarios:
Scenario 1: From specification to implementation.
Scenario 2: Reusing and re-engineering non-ontological resources (Psychology Theory, Lexicon, Thesaurus).
Scenario 3: Reusing ontological resources.
Scenario 4: Reusing and re-engineering ontological resources.

Sources of Knowledge: Non ontological resources (lexicon, thesaurus), and psychological theories(book ,research paper).
Ontological resources (existing related ontologies)

Figure 4.2: HASIO specification document.

the reusing and reengineering of ontological and non-ontological resources like psychology theory, lexicons and thesauri. The non-ontological aspect is the specification starting point for implementation. reengineering non-ontological resources includes converting non-ontological sources of knowledge into the format of an ontology. This step may include changing the class structure, or changing the class name to follow the new ontology's patterns. Ontological reuse can be accomplished by reusing the whole ontology or only some of its classes. reengineering ontological resources is also done when fixing issues or locally editing the reused existing ontologies. In our case, we locally edited the reused ontologies FOAF and HEO. The reason we chose to edit them is because of the Punning problem [128]. This problem can occur when the same name is used to declare both an object and a data property, which constitutes an illegal redeclaration of entities. For example, in FOAF the entities : aim- ChatID, and yahooChatID have illegal redeclaration, because they used as object properties and data properties. We changed the names of the conflicting entities (either the object property or the data property) without changing the structures or the intention of the ontology.

The ontology specification document further includes the ontology Competency Questions (CQs), which will be introduced in Section 4.1.6. CQs help to define the scope of the ontology, and thus aid in information acquisition and development.

4.1.2 HASIO Knowledge Acquisition

Since the proposed ontology represents human affective states and their influences, HASIO uses psychological theories, and existing ontologies from the same domain. HASIO also uses a lexicon and a thesaurus that cover human affective states as a source of knowledge, as stated in Section 3. Even though the knowledge acquisition consider as a main step in the ontology engineering, it still done simultaneously during other steps such as the construction of the ontology specification document and conceptualization.

4.1.3 HASIO Conceptualization

HASIO is based on many psychological theories. Its goal is to conceptualize these theories in a meaningful and computerized format. During the conceptualization phase, the domain knowledge of the HASIO model is organized into a conceptual model that lets the ontology answer the the questions proposed in the CQ document. The conceptualization of HASIO was an iterative process. As a result, a number of previous models underwent a great deal of changes before arriving at the ontology conceptualization presented here.

The conceptual model starts with a glossary of terms taken from existing related psychology theories and ontologies , and then groups the terms into classes and subclasses (concepts) and properties (verbs). Based on the CQs, Figure 4.3 shows the main entities in HASIO and the relationships between the entities.

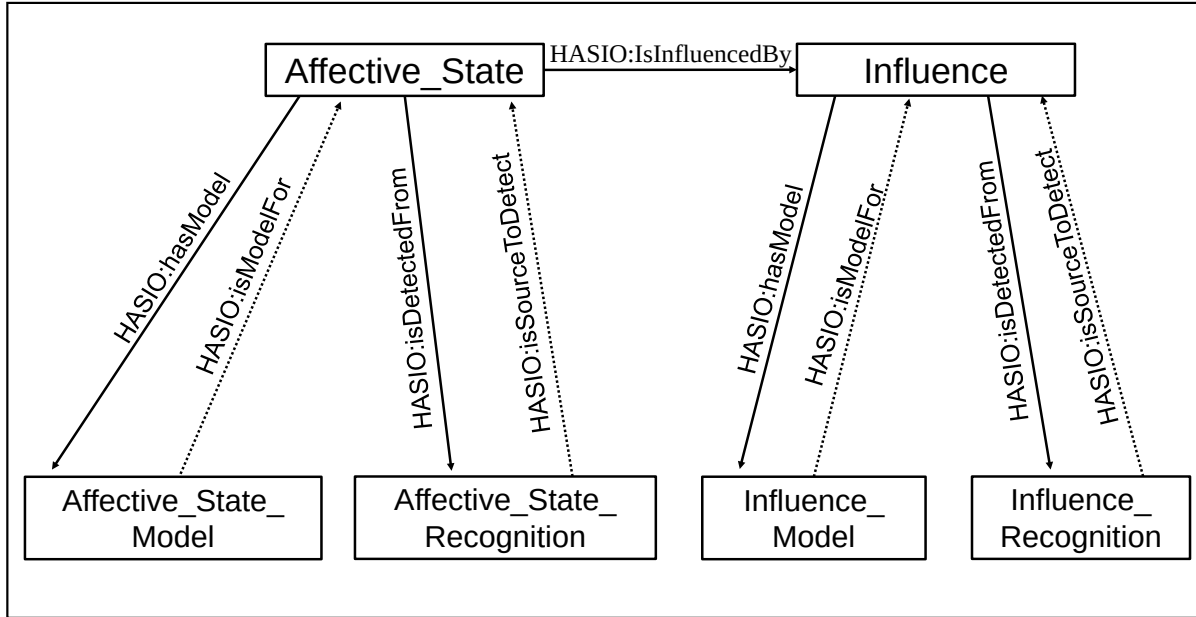


Figure 4.3: Conceptual model of the HASIO depicting the major entities. Rectangular shapes represent classes, arrows indicate object properties, and dotted arrows indicate the inverse of object properties.

The class *Affective State* represents human affective states. The ones considered here are Emotion, Mood, and Sentiment. The *Affective State Model* represents the psychological models for each affective state as discussed in Chapter 2. *Affective State* thus has a relationship with the class *Affective State Model* through the "hasModel" relationship. Analogously, *Affective State Model* connects to the *Affective State* class through the "isModelFor" relationship. *Affective State Recognition* represents the ways or methods to detect each affective state. Thus, an *Affective State* "isDetectedFrom" an *Affective State Recognition* method.

The class *Influence* in the ontology represents the influences on human affective states. We consider Need, Personality, and SWB as the influencing factors. Each factor can in turn be represented by an *Influence Model*, which is represented by the class of the same name. In the on-

tology, this is expressed as a "hasModel" relationship that connects *Influence* with the *Influence Model*. Similar as in the case of affective states, the class *Influence Recognition* represents the ways or methods used to detect each influence. Accordingly, *Influence* connects with an *Influence Model* through a "isDetectedFrom" relationship.

As described in Chapter 2, Need, Personality, and Subjective well-being are factors that influence Emotion, Mood, and Sentiment. This is modeled as an additional "isInfluencedBy" relationship between *Affective State* and *Influence*.

4.1.4 HASIO Integration

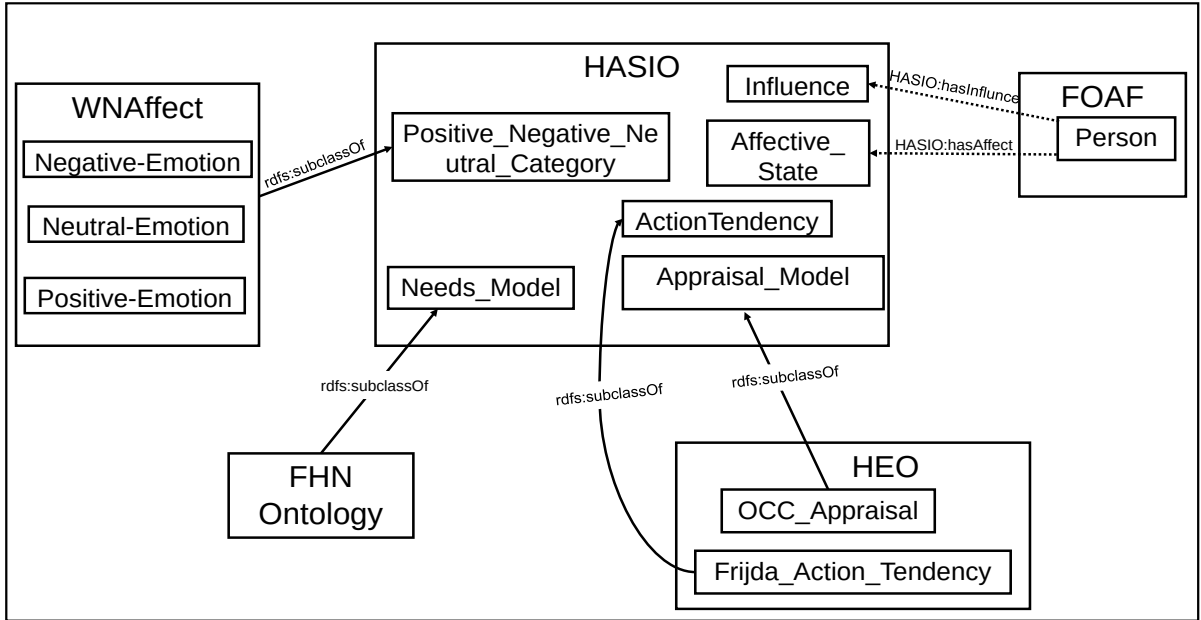


Figure 4.4: Linking HASIO to the imported ontologies. Rectangular shapes represent classes, solid arrows indicate a subclass relationship, and dotted arrows indicate object properties.

Our proposed ontology benefits from reusing and reengineering existing ontologies. After analyzing the existing ontologies, we chose those which met our purpose and proposed ontology requirements. We reused them in their entireties or incorporated selected classes. WordNet-Affect Taxonomy (WNAffect) was reused because it classifies emotion words into positive, negative and neutral, so we integrated them under the subclass *Positive_Negative_Neutral_Category*. We

reused the whole Fundamental Human Needs Ontology (FHN) under the class *Needs_Model*. Furthermore, from the Human Emotions Ontology (HEO) we reuse the classes : *OCC_Appraisal*, and *Frijda_Action_Tendency* to include them under the classes: *ActionTendency* and *Appraisal_Model* respectively. Since human affective states and their influences affect the person, we reused Friend Of A Friend (FOAF) to represent this relation. Figure A.14 shows the imported ontologies and illustrates the links between them and HASIO.

4.1.5 HASIO Implementation

The implementation phase involves the selection of a suitable environment. HASIO was developed with the Web Ontology Language (OWL) ³ by using the Protégé tool. Protégé⁴ is an open source tool for ontology development that supports OWL. It allows users to create, edit, visualize and evaluate an ontology. Furthermore, Protégé allows the importing of existing ontologies. We took the advantage of OWL and Protégé to develop and evaluate HASIO.

Ontology metrics is one of Protégé features. The metrics show the ontology information such as: axiom count, individual count, inverse object properties count, class assertion and annotation assertion count. In addition, the metrics show the ontology family (DL expressivity). HASIO DL expressly belongs to ALCROIF family [15]; which can be broken down into the following:

AL : Attributive language.

C: Complex concept negation.

R: Limited complex role inclusion axioms; reflexivity and irreflexivity; role disjointness.

O: Nominals. (Enumerated classes of object value restrictions: owl:oneOf, owl:hasValue).

I: Inverse properties.

F: Functional properties.

So, HASIO has attributive language (basic DL language) with additional features such as negation, disjoint, complex roles, object value restrictions, inverse properties and functional properties.

4.1.6 Competency Questions

An important task in the Methontology involves creating Competency Questions (CQs). Outlining a list of questions that an ontology should be able to answer is a means of defining scope.

³<http://www.w3.org/TR/owl-features/>

⁴<http://protege.stanford.edu/>

These questions are later used to test and evaluate the ontology in order to check if it contains enough information to answer the CQs. Coming up with CQs was a combination of analysis and brainstorming, taking into consideration the purpose of HASIO development and analyzing resources from psychology theories, available lexicons and existing ontologies. There were many iterations until we came up with the CQs list. Furthermore, ontology applications play an important role in determining the CQs list. Our ontology was constructed with regard to the domain of human affective states and their influences, and by using psychological theories as knowledge sources. As such, the following CQs formed the basis for HASIO:

1. What are the Affective States?
2. What are the Influences on the Affective States?
3. What are the possible Affective States models?
4. What are the possible Personality models?
5. What are the possible Need models?
6. What are the possible Subjective well-being models?
7. What are the methods to collect information about Emotion?
8. What are the methods to collect information about Mood?
9. What are the methods to collect information about Sentiment?
10. What are the methods to collect information about Personality?
11. What are the methods to collect information about Need?
12. What are the methods to collect information about Subjective well-being?
13. What are the causes of Emotion?
14. What are the causes of Mood?
15. What are the dimensions of Emotion Action Tendency?
16. What are the ways to express human Emotion?

4.2 HASIO Class-Subclass Structure

We developed HASIO by using a top-down development process approach. This approach started with the main concept in the domain and then we created the subclasses [133]. For example, we

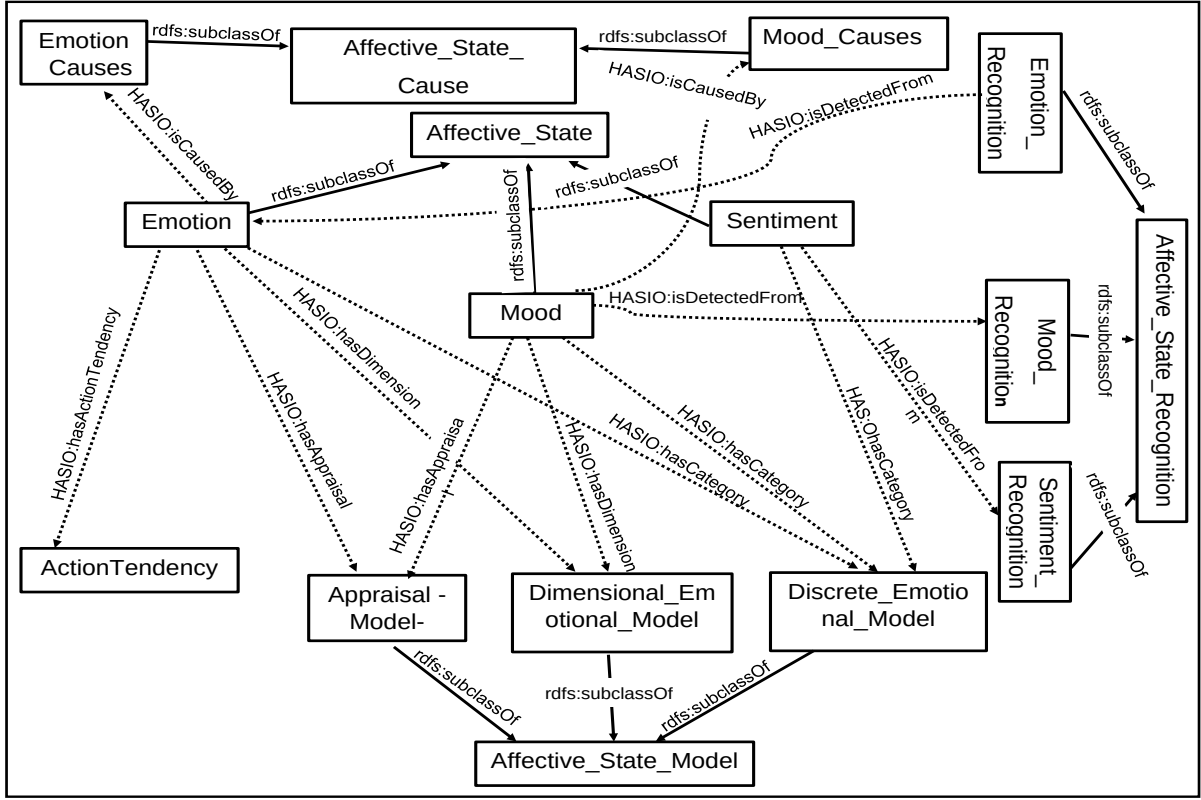


Figure 4.5: Graphical representation of the main classes of HASIO and the properties. Rectangular shapes represent classes, solid arrows indicate subclass relationships, and dotted arrows indicate object properties.

created the class *Affective_State*, then we created its subclasses (*Emotion*, *Mood*, and *Sentiment*). In this section we present the HASIO class-subclass structure that makes up the main part of the ontology. Figure 4.5 shows the main classes of HASIO that relate to affective states.

Humans have *Mental States* and *Physical States*. *Mental States* which represent the *Affective states* can be divided into three sub-classes: *Emotion*, *Mood*, and *Sentiment*. *Human Affective States* can be influenced by *Need*, *Personality*, and *Subjective well-being* by using the property "isInfluencedBy". These influences are subclasses of the *Influence* super-class.

To express the ways of representing the affective states, we created the *Affective State Model* class. An *Emotion* can be described in a discrete way by using the property "hasCategory", in a dimensional way by using the property "hasDimension", and in a componential way by using the

property "hasAppraisal" [95].

When defining emotion in a discrete way, we introduce subclasses under the *Discrete Emotional Model*. One of the common subclasses is *Basic Emotion Category*. In addition, HASIO contains a subclass to express the emotion classified by the model of Douglas-Cowie, and reused emotion vocabularies defined by EmotionML. These vocabularies were clustered in groups, but HASIO expresses them in the subclasses of *Every Day Emotion Category*, *OCC Emotion Category*, *Frijda Category*, and *FSRE Category*. HASIO also includes a *Social Emotion Category* subclass to represent social emotions. Moreover, HASIO defines subclasses under the *Discrete Emotional Model* based on Drummond's emotion vocabulary. They are categorized under the *Drummond Category* subclass.

Based on the Drummond Emotion Vocabulary, we created a *LevelOfEmotion* subclass where emotion can be classified as *Light*, *Medium*, or *Strong*. The emotion vocabulary in HASIO connects with the above-mentioned subclass through the property "hasLevel". The *Positive Negative Neutral Category* subclass was created to include information from WordNet, Parrott Vocabulary, NRC Word-Emotion Association Lexicon, WordNet-Affect, Tom Drummond Emotion Vocabulary and Oxford English Dictionary.

Emotion can be defined by existing dimensional models. HASIO represents these models by including the subclasses named *Circumplex Model*, *Fontaine Model*, *PAD Model*, and *Watson and Tellegen Model* under the super-class *Dimensional Emotional Model*.

Additionally, an emotion can be expressed by a componential model. HASIO represents *OCC Appraisal* as a subclass of the class *Appraisal - Componential Model*. The *OCC Appraisal* subclass was reused from the HEO ontology.

Due to the similarities between mood and emotion, mood can also be expressed by a discrete or a dimensional model [107]. Hence, the *Mood* class connects to the *Discrete Emotional Model* and the *Dimensional Emotional Model* subclasses through the properties "hasCategory", and "hasDimension". Furthermore, *Sentiment* can be represented by a discrete model through the *Positive Negative Neutral Category* subclass.

An emotion can have an action tendency which defines the emotion action outcome. It is expressed through the property "hasActionTendency". HASIO defines the *Frijda Action Tendency* as a subclass of the *Action Tendency* class.

To include the ways in which humans express emotion, the *Emotional Expression Cue* super-class was added to HASIO. Its sub-classes are *Conductual Emotional Cues*, *Physiological Emotional Cues*, *Textual Emotional Cues*, and *Verbal Emotional Cues*, which is in line with the emotion ontology by Obrenovic et al. [134]. *Conductual Emotional Cues* are further structured into facial expressions, gestures and speech. The relationship between *Emotions* and their Emotional Expression Cues is modeled by the property "isExpressedThrough".

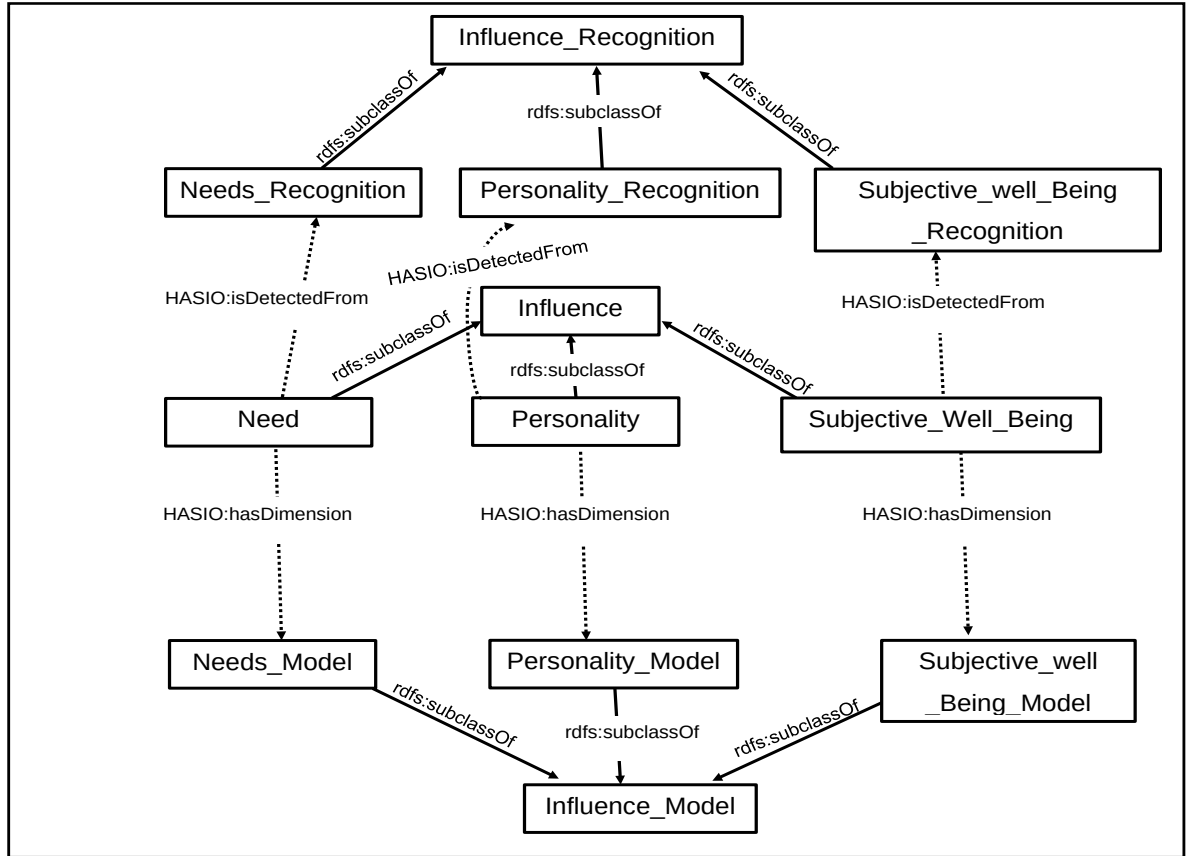


Figure 4.6: Graphical representation of HASIO's classes that are related to the influences of affect. Rectangular shapes represent classes, solid arrows indicate subclass relationships, and dotted arrows indicate object properties.

To include the causes for mood and emotion, we created the *Affective State Cause* class. *Emotion* and *Mood* are connected to *Emotion Causes* and *Mood Causes*, respectively, through the property "isCausedBy".

HASIO proposes an *Affective State Recognition* class to model the possible ways of collecting information to identify human affective states. Therefore, *Emotion*, *Mood*, and *Sentiment* connect to *Emotion Recognition*, *Mood Recognition*, and *Sentiment Recognition*, respectively, through the "isDetectedFrom" object property.

HASIO introduces the *Influence Model* as a super class for the *Personality Model*, the *Subjective*

well-being Model, and the *Needs Model* subclasses. The *Big Five Personality Traits* subclass is a subclass of the *Personality Model*. Under each personality trait, there are two subclasses: *Positive Pole*, and *Negative Pole*. The positive pole contains all adjectives that indicate a high score in the respective trait while the negative pole contains the ones with a low score.

We adopted the adjective lists from [99], and [77].

Life Satisfaction, *Pleasant Affect*, and *Unpleasant Affect* are all components of the *Subjective Well-Being Model*. The subclasses *Personality*, *Subjective Well-Being*, and *Need* are connected to the *Personality Model*, the *Subjective Well-Being Model*, and the *Needs Model*, respectively, through the property "hasDimension".

There exist many *Need* models in the literature. HASIO models two of them as sub-classes. The theories are *Fundamental Human Needs*, and the *Self-Determination Theory*. The former has previously been modeled by the FHN ontology, which is reused by HASIO.

HASIO expresses how to detect the influences in the *Influence Recognition* class. Consequently, *Need*, *Personality*, and *Subjective Well-Being* are connected to *Needs Recognition*, *Personality Recognition*, and *Subjective well-being Recognition*, respectively, through the "isDetectedFrom" object property. Figure 4.6 displays the main classes of HASIO that are related to the influences of affect. Furthermore, HASIO demonstrates the relations between *Emotion*, *Mood*, *Need*, *Personality*, and *Subjective Well-Being*. Figure 4.7, and Figure 4.8 illustrate the object properties between emotion, mood, needs, personality and SWB.

Since affective states and their influences are expressed by and affect people, we reused the FOAF ontology. The subclass *Person* in FOAF is connected to HASIO through object properties such as "hasMentalState", and "hasPhysicalState".

As we propose to use HASIO for sentiment analysis, we give more details and a visualization of the "Discrete Model" class-subclass. Figure 4.9 shows the Discrete Model class-subclass Visualization. It shows the hierarchy, object properties and data properties. The Positive Negative Neutral Category and Psychological Theories are subclasses of Discrete Model. The Psychological Theories are: Basic Emotion Category, Douglas-Cowie Category, Drummond Category, Every Day Emotion Category, Frijda Category, FSRE Category, OCC Emotion Category and Social Emotion Category.

The "Affective State Polarity" class was created with three individuals: negative affective state, positive affective state and neutral affective state. Moreover, we added individuals for each "Discrete Model" subclass, which are the words extracted from dictionaries, lexicons and psychological theories. Each individual can belong to more than one subclass, particularly if one of them is the Positive Word, Negative Word or Neutral Word subclass. In addition, we created a data property "strength score" with a range of `xsd:integer [-5,5]`. We extracted all the individual strength scores from SentiStrength and AFINN. For example, the individual "happy" has a

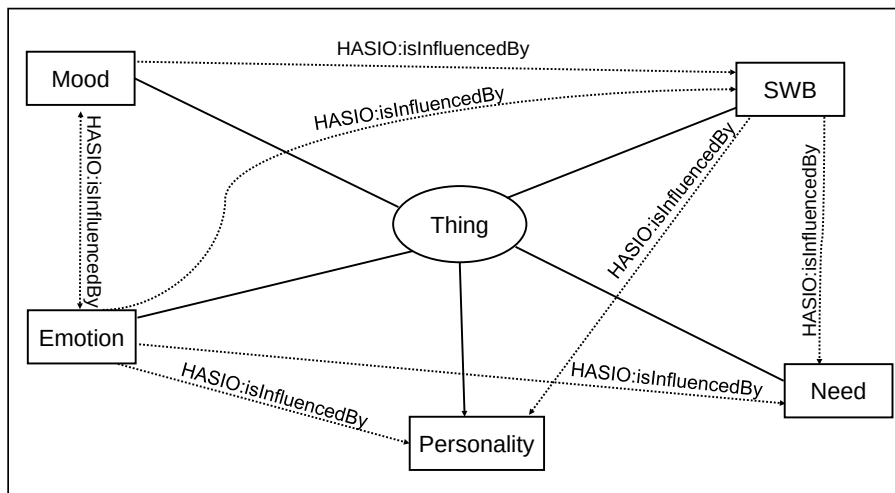


Figure 4.7: Relationships between Emotion, Mood, Personality, SWB, and Need. Rectangle shapes represents classes, and dotted arrows indicate relationships.

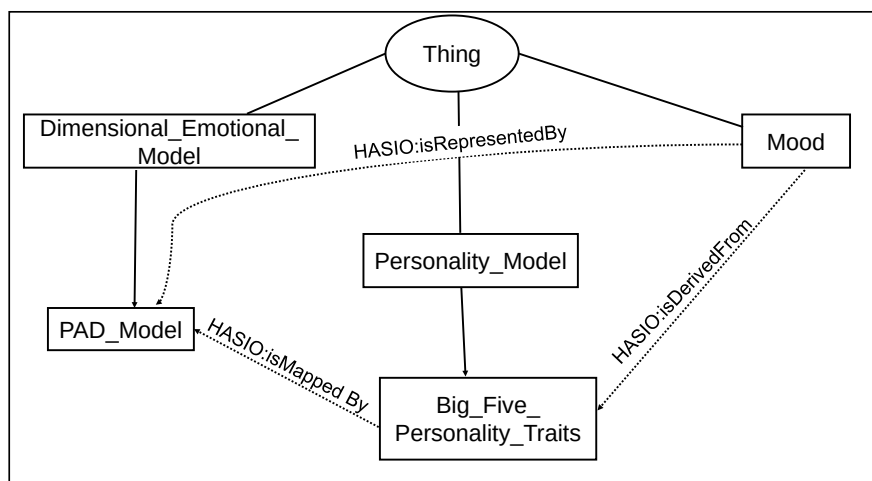


Figure 4.8: Relationships between Emotion, Mood, and Personality. Rectangle shapes represents classes, and dotted arrows indicate relationships.

strength score of 2, the individual "sad" has a strength score of -4 and the individual "scholarship" has a strength score of 0. HASIO covers a wide range of words, so if we do not find the strength score of the individual word in any of the lexicons, we assign the strength score of one

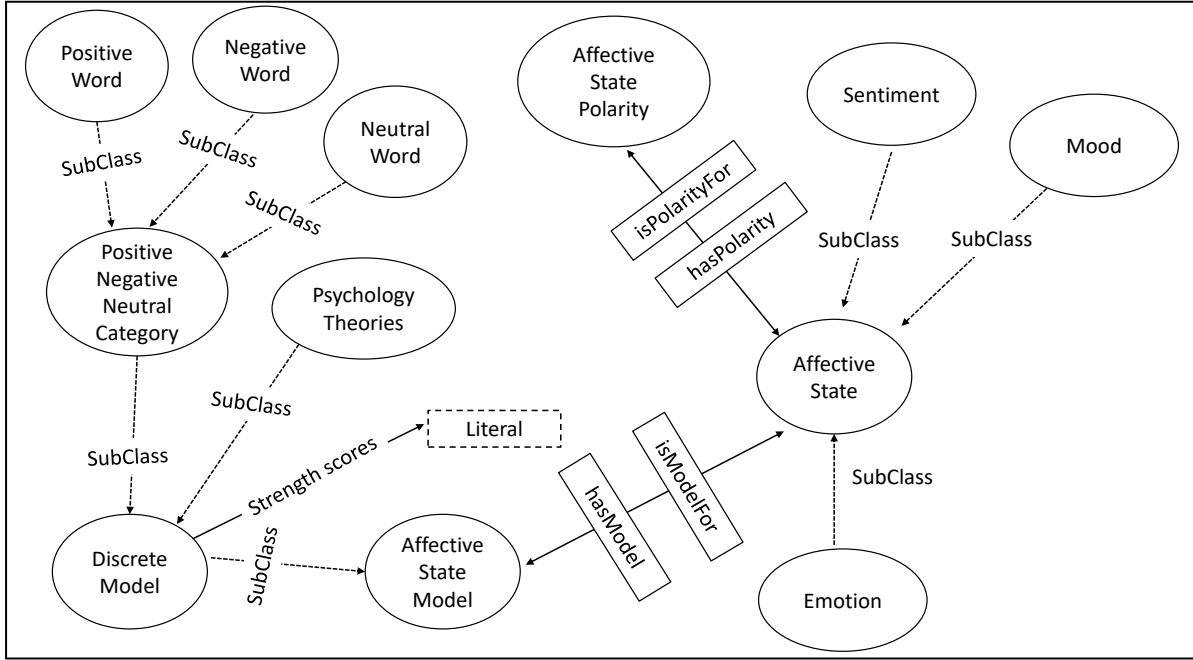


Figure 4.9: Discrete Model class-subclass Visualization. Oval shape represents class , and sub-class , rectangle shape represents object property, and round dot rectangle represents data property.

of its lexicon-derived synonyms .

4.3 HASIO Object Properties

Specifying the properties in HASIO was vital in order to conceptualize the ontology and to answer the assigned questions. Object properties define the relationships between individuals. A short outline of the major HASIO object properties was given in Section 4.2. In this section, we analyze the object properties defined in HASIO by showing the domain, range and inverse-properties of a selection. Table 4.1 illustrates the property name, domain, range and inverse of properties.

Table 4.1: A selection of properties used within HASIO. Domain, range and inverses are given as well.

Property Name	Domain	Range	Inverse Of
hasbehavior	Person	Behavior	isBehaviorOf
hasEmotion	Person	Emotion	isEmotionFor
express	Emotional Expression Cue	Emotion	isExpressedThrough
hasActionTendency	Emotion	Action Tendency	isActionTendencyOf
hasAppraisal	Emotion or Mood	Appraisal - Componential Model	isAppraisalOf
hasNeed	Person	Need	isNeedFor
hasSubjectiveWellBeing	Person	Subjective Well-Being	isSubjectiveWellBeingFor
hasPersonality	Person	Personality	isPersonalityFor
hasMentalState	Person	Mental State	isMentalStateof
hasModel	Affective State or Influence	Affective State Model or Influence Model	isModelFor

4.4 HASIO SWRL

HASIO defines the concepts and relationships for Human Affective States and Influences domain. Consequently, it is clear that HASIO is not just a plain taxonomy or hierarchy of concepts; by contrast, ontologies do not permit for the level of expressiveness required regarding decidability. Rules accomplish this job more effectively. As a result, HASIO is extended by as set of SWRL that are based on logic programming. In many cases ontologies by themselves are not enough, while a combination of OWL and SWRL is very beneficial. Ontologies represent the "terminological" part of a domain and SWRL represents the "deductive" part of the knowledge. SWRL is a combination of OWL DL + Rue ML (Markup Language) (XML Language). SWRL expresses itself in terms of OWL concepts (classes, properties, individuals) [73]. HASIO rules were formulated to represent several expressive statements. For instance, when a person experiences a bad mood, his emotion may be negative as a consequence [31] ; this statement can be stated with SWRL as:

```
foaf : Person(?p) ∧ HASIO : associated_Mood(?e, "negative" ∧ ∧rdf : PlainLiteral) ∧
HASIO : Emotion(?e) ∧ HASIO : hasEmotion(?p, ?e) ∧ HASIO : hasMood(?p, ?m) ∧
HASIO : Mood(?m)
→ HASIO : associated_Emotion(?m, "negative" ∧ ∧rdf : PlainLiteral)
```

Another example is that feelings and emotions are generated by needs, and can therefore serve as a guide to identify a person's state of needs-satisfaction. It also identifies positive and pleasant emotions, such as feeling delighted and thankful, that arise when needs are met [148]. This statement can be stated with SWRL as:

```
HASIO : Need(?n) ∧ foaf : Person(?p) ∧ HASIO : hasNeed(?p, ?n) ∧
HASIO : Needs_Satisfied(?n, "yes" ∧ ∧rdf : PlainLiteral)
→ HASIO : associated_Emotion(?p, "positive" ∧ ∧rdf : PlainLiteral)
```

4.5 HASIO Modularization

In many domains, ontologies can have thousands of axioms to cover concepts and topics. Nevertheless, large ontologies can face problems of scalability, reusability and validation. Dividing the ontology into self-contained modules that handle sub-topics from the large ontology can solve many of these problems. This activity is called Ontology Modularization. According to the NeOn dictionary, it is the activity that takes as an input an ontology and produces modules for this ontology to support maintenance and reuse [170]. Ontology modularization has two approaches: ontology partitioning and module extraction [44]. The first approach divides the ontology into a set of modules, such that the union of all the modules is equal to the original ontology. Module extraction, however, reduces the ontology into sub-parts, each part containing a sub-vocabulary. This approach can be considered when the determination relates to extracting specific parts of an ontology. HASIO covers a wide range of human affective states and influences, indeed many topics. Through modularization, we create modules that handle parts of the ontology and follow the tasks that were determined in [43].

Task 1: Identify the Purpose of Modularization

Recognizing the need for modularization is vital and will guide the whole process. The purpose of modularizing HASIO is to facilitate the processes of understanding the ontology as whole, as well as maintenance, reusability and validation. This can be accomplished by producing modules of a manageable size, such that each module covers a subtopic of HASIO

Task 2: Select a Modularization Approach

The approach can be determined based on the modularization purpose.

However, the modularization process can be performed in an iterative manner based on the modularization criteria, which is the next task. We chose the partitioning approach and divided HASIO into modules; each module handles a part of HASIO. This process produces modules of a controllable size.

Table 4.2: HASIO modules after the second iteration of modularization

Module	Module Name	Class Count	Properties Count
Original Ontology	HASIO	274	218
M1	Influence Model	90	41
M2	Influence Recognition	11	2
M3	Affective States Recognition	33	2
M4	Affective States Influences Relations	33	92
M5	Emotion Expression Cues	53	22
M6	Affective States Causes Reaction	35	7
M7	Affective States Dimensional Model	11	8
M8	Affective States Appraisal Model	20	6
M9	Affective States Discrete Model	38	13
M10	Affectional	13	6

Task 3: Define Modularization Criteria

Based on the purpose of the HASIO modularization, we chose the criteria of **local correctness** and **size** [45] Local correctness means that nothing is added to the modules that were not originally in the ontology. The size of a module represents the number of classes, properties and individuals contained therein, and can determine its maintainability in the future.

Task 4: Select a Base Modularization Technique

There are many techniques and tools for ontology modularization. We chose to use the "copy/move/delete axioms" functionality in Protégé to achieve HASIO modularization.

Task 5: Combine the Results

In this step, modules are generated by using the "copy/move/delete axioms" functionality as a first iteration.

Task 6: Evaluate the Modularization

Modules were evaluated against the HASIO modularization criteria. The evaluation outcome determines if a new iteration needs to be carried out. It can also indicate whether another modularization approach should be applied or not. After evaluating the HASIO modules, we found that Affective States Discrete Model contradicted the purpose of modularization as its size was not manageable.. As a result, one more iteration was performed. Here, we used the approaches of partitioning and extraction, respectfully. At the end of the second iteration, the evaluation yielded satisfactory results.

Task 7: Finalize Modularization

When the outcome of the evaluation is acceptable, the output is all of the modules that were produced from the modularization process. Table 4.2 shows the modules of HASIO after applying the second iteration of modularization. M10 can be used in affective states analysis. This module can be further divided into three modules: Positive, Negative and Neutral, based on the applications purpose.

HASIO modularization modules can be downloaded under the link: <https://github.com/ranaothman/HASIO-Modularization>

4.6 Conclusion

In this chapter we presented the development of HASIO, a tool that delivers knowledge and a common vocabulary in a machine-accessible or machine-readable format regarding human affective states (emotion, mood, sentiment) and their influences (need, personality, and SWB). There is no standard way to build an ontology, however, understanding the need and the requirements of the proposed ontology allowed us to select the appropriate method to follow. We selected Methontology since it aided us to develop HASIO and achieve our goal. It is recognized as a well- established methodology that supports the building of an ontology.

Selecting the ontology development features was based on the knowledge and the relationships that needed to be represented. HASIO has attributive language (basic DL language) and has features such as negation, disjoint, complex roles, object value restrictions, inverse properties and functional properties.

Methontology permitted us to specify HASIO metadata and this step helped in stating the goal and representing knowledge. As a result, the processes of reusing and extending were simplified. HASIO profits from its ability to reuse existing ontologies and saves time in the development and maintenance process. Coming up with a suitable conceptualization model lead to recognizing the specific axioms that fulfilled our ontology requirements as well as having enough of them to answer the CQs correctly.

A significant task in the Methontology involves creating Competency Questions. They define the scope of the ontology and determine the axioms needed or it to be able to answer all the CQs. Coming up with the CQs resulted from a combination of brainstorming, considering the purpose of HASIO development, and analyzing resources from psychological theories, available lexicons and existing ontologies. As ontology does not have a decidability aspect, therefore we extended HASIO with some SWRL rules. A combination of OWL and SWRL are very beneficial for creating a semantic application that requires expressiveness and decidability.

Since HASIO covers a wide range of topics, it has a large number of axioms. Consequently, dividing HASIO in modules helps in scalability, reusability and validation. Validating a large ontology can result in incompleteness. In Chapter 5 we validate HASIO modules to insure the overall quality of the ontology.

Chapter 5

HASIO Evaluation

The growing interest in building ontologies increases the need for their evaluation. Ontology evaluation can be defined as the process of determining quality with respect to specific criteria [88]. This process aids developers in deciding which ontology to reuse. We evaluated HASIO for verification and validation; for the former we used OOPS!, a web- based tool that scans for major pitfalls. For the latter, we used the CQs presented in Section 4.1.6, to validate that the major requirements of the ontology were satisfied. We also verified HASIO’s consistency by running a Pellet reasoner.

In Section 5.1, we present the OOPS! evaluation on the HASIO modules and its results. In Section 5.2, we present the results of the SPARQL Query regarding HASIO CQs and in Section 5.3, we present the Pellet reasoner results. Next in Section 5.4, is HASIO and HASIO Modules Accessibility process. We highlight HASIO and its modules evaluation in Section 5.5

5.1 HASIO Modules Evaluation Result by OOPS!

In this section we discuss the results of the HASIO modules after parsing them through Ontology Pitfall Scanner (OOPS!) OOPS! is a Java web-based application ¹. The web user interface allows the ontology URI to be entered or the RDF document to be analyzed. The ontology is scanned, seeking pitfalls from those identified in the OOPS! pitfall catalogue. After that, the list of pitfalls, if any, are presented with affected ontology elements as well as pitfall explanations [141]. OOPS! evaluation options are divided into two main categories [142]:

¹ <http://oops.linkeddata.es/index.jsp>

Classification by Dimension

- **Structural Dimension**
this dimension focuses on syntax and formal semantics. It looks for pitfalls such as: defining wrong equivalent properties, defining wrong inverse relationships, missing domain or range in properties.
- **Functional Dimension**
this dimension focuses on ontology conceptualization. It looks for pitfalls such as Creating unconnected ontology elements or Missing disjoints.
- **Usability-Profiling Dimension**
this dimension refers to communication context of an ontology, when an ontology offers information that eases understanding of it. It looks for pitfalls such as Missing annotations or Inverse relationships not explicitly declared.

Classification by Evaluation Criteria

- **Consistency**
in this Criteria the tool looks for issues that hamper the consistency of the ontology, such as defining wrong inverse relationships, defining multiple domains or ranges in properties.
- **Completeness**
in this Criteria the focus is on looking for expected information that should be in the ontology, such as creating unconnected ontology elements or inverse relationships not explicitly declared.
- **Conciseness**
in this Criteria the tools seek pitfalls related to class and relationship design, such as using synonym classes and miscellaneous classes.

OOPS! identified three pitfalls level [75]:

- **Critical** the pitfall has to be addressed and corrected or it will affect ontology consistency.
- **Important:** although it is not critical for ontology function, it is important to correct this type of pitfall.
- **Minor:** although It does not cause a problem, correcting the pitfall makes the ontology more well-organized and user-friendly.

Evaluation is a continuous process during the development and engineering of the ontology, therefore multiple scans were performed by OOPS! on the HASIO modules.

Table 5.1: OOPS! evaluation pre and post correction

OOPS! Evaluation	Pre-Cor	Post-Cor
Structural Dimension Classification	100	61
Functional Dimension Evaluation	11	6
Usability Profiling Dimension	1641	811
Consistency Criteria	3	2
Completeness Criteria	81	55
Conciseness Criteria	0	0

In the structural dimension evaluation, merging different concepts into the same class caused a pitfall. For example, the *Watson and Tellegen Model* subclass in the *Affective States Dimensional Model Module* contains two names (Watson and Tellegen) which differ from the name style of other sub-classes. However, this name represents a psychological theory, so for this reason we presented the subclass with this term.

The most pitfalls occurred in the functional dimension evaluation as a result of creating unconnected ontology elements. This pitfall is minor within OOPS! classification, however we do address it in the modules. Missing annotation was one of the pitfalls in the usability profiling dimension, as we added many comments and explanation in the annotation portion. Yet, the number of pitfalls in this criterion are still high.

Regarding the consistency criteria, merging different concepts into the same class caused a pitfall in the *Affective States Dimensional Model Module* and the *Affective States Causes Reaction Module*; such as the subclass *Safety_and_security* in *Affective States Causes Reaction Module*. The Completeness Criteria pitfalls in HASIO were caused by inverse relationships not explicitly declared and by missing disjoints. However, not all object properties need inverse relationships and not every class and subclass needs a disjoint declaration. For example, the object property *isDerivedFrom* represents the relation between *Mood* and *Big five personality Traits*. However, the inverse relation is not true and cannot be applied.

Classes are disjoint if they cannot have any shared individual. In HASIO there are some disjoint classes, but other classes are not disjoint. For example, an individual happy can belong to Emotion, Mood and even Personality.

Overall, we addressed all major and important pitfalls as well as minor ones that affected HASIO module requirements and purposes. OOPS! was able to scan minor and critical pitfalls that were missed during ontology and module design. This allowed us to fix the pitfalls after detecting them. Table 5.1 shows the total number of pitfalls before and after our correction for all of the HASIO modules.

5.1.1 Other Modules Evaluation

Additional modules exceeded the size that could be handled by OOPS!, therefore, we evaluated them manually by following the catalogue for ontology diagnosis [140]. We found that the modules were free from critical pitfalls, such as creating the relationship "is" instead of using "rdfs:subclassof," defining wrong inverse relationships, and defining multiple domains or ranges in properties. The modules are not missing domains or ranges in properties, nor do they use recursive definitions. For minor pitfalls, the modules do not merge different concepts into the same class, or explicitly declare the inverse relationships. However, the modules lack annotation and a label.

5.2 HASIO Evaluation via Competency Questions

Competency questions (CQ) played a significant role in the evaluation of HASIO after its implementation. CQs are used as a reference to confirm whether or not an ontology satisfies its requirements. In [114], Malheiro and Freitas stated the importance of CQs to create and evaluate an ontology.

Camila Bezerra et al. also acknowledged the significance of evaluating ontologies via competency questions. They proposed an algorithm that, given a CQ in natural language, checks whether or not the ontology answers to CQ [24].

In order to do this, we designed a HASIO Question Answering system (HASIOQA)²: a task-based evaluation system with a natural language interface. SPARQL language can be used to query the ontology [103]. The system receives as input a question expressed in English and then converts it to SPARQL query. As a result, the query will be run against a HASIO. The evaluation will achieve two goals: A comprehensive evaluation of the HASIO and overcoming the complexity and difficulty of SPARQL Query by using a natural language user interface.

5.2.1 Setting Up HASIO Question Answering system

The system receives as input a question expressed in English and then convert the question to SPARQL query to retrieve the answer from the HASIO. The architecture of the system is demonstrated in Figure 5.1.

²The Java based application for the system can be found under : <http://www.mcrlab.net/datasets/>

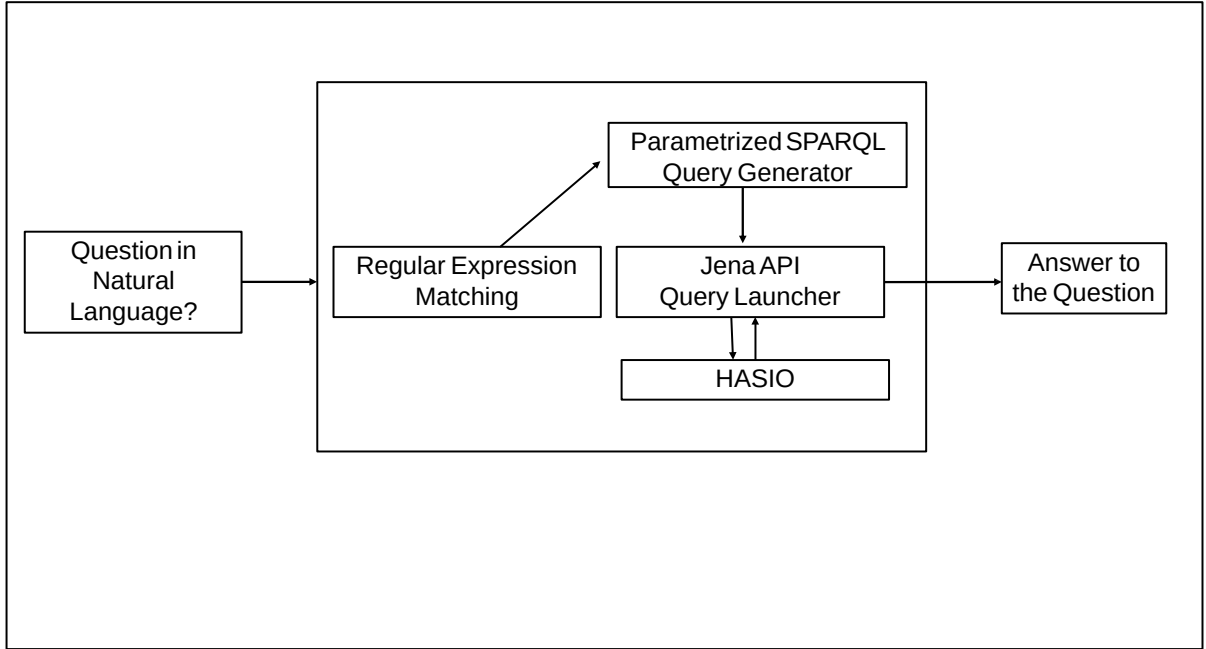


Figure 5.1: Natural Language Interface to HASIO System architecture.

The system tackles the HASIO CQs and other secondary questions that can be extracted. The implementation uses Eclipse environment and Jena Ontology API ³. Apache Jena is an open source Semantic Web framework for Java. It provides an API to extract data Ontology [34] First, we defined regular expressions to match the natural language questions. Then we defined a parameterized SPARQL Query to run a query against HASIO through Jena, based on the user natural language question. HASIO represents physiological theories for Emotion, Mood, Sentiment, Need, Subjective well-being and Personality. Table 5.2 shows a sample list of questions and regular expressions.

5.2.2 Evaluating CQs with HASIO Question Answering system

We ran the system and evaluated the answers for each HASIO CQ represented in Chapter 4. Based on the reading and understanding, our SPARQL results from the proposed ontology are in line with results from psychology resources and theories.

³ <https://jena.apache.org/documentation/ontology/>

Table 5.2: Questions in natural language for retrieving answers from HASIO

ID	Template	Sample Question
Q1	List the well known *	List the well known Emotion Action Tendency theory?
Q2	What are the possible *	What are the possible Affective States Models?
Q3	What are the causes of *	What are the causes of Mood?
Q4	What are the ways to express *	What are the ways to express Human Emotion?
Q5	List the emotion vocabularies classified by *	List the emotion vocabularies classified by Inadequateness Drummond Category?

5.3 Results of the Pellet Reasoner

Ontology reasoning is based on the Open World Assumption (OWA), signifying information that has not explicitly been added is assumed to be missing and can be added later. That way, a reasoner can infer more axioms in the ontology [150]. We ran the Pellet reasoner throughout the HASIO development process and it reported errors due to the Punning problem. Eventually, we corrected these error as mentioned in Section 4.1.1. Pellet was also run throughout the creation of HASIO modules. The reasoner was able to infer new axioms not directly asserted by us, such as inferring a new axiom for the individual type. Table 5.3 illustrates the total number of asserted and inferred axioms in each HASIO module.

Some modules have a high Inferred Axiom number; this is because the Pellet reasoner inferred a new axiom reading individuals. It infers their type to be the superclass of its current type; for example, in Affective States Discrete Model, the individual "zippy" has asserted an axiom that is a type of Happiness_Drummond. Happiness_Drummond has superclass Drummond_Category, which has superclass Discrete_Model. Pellet inferred that "zippy" has flowing Inferred Axioms: zippy Type Discrete_Model zippy Type Drummond_Category.

Figure 5.2, and Figure 5.3 show inferred axioms in some HASIO modules. The class hierarchy section shows class-subclass structure (asserted), while the classification results section shows pellet axioms inference (inferred).

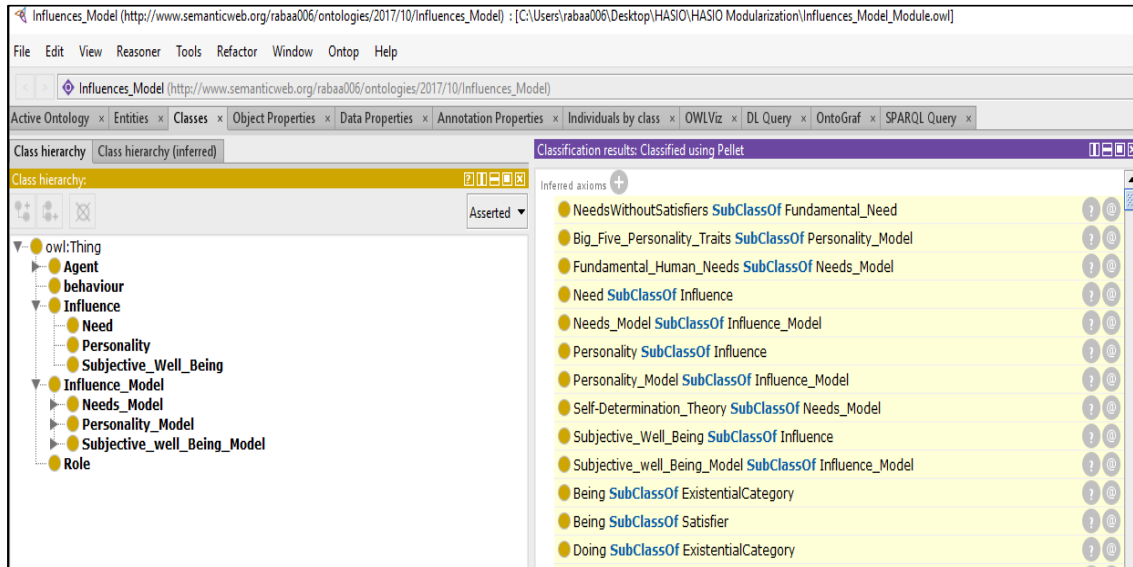


Figure 5.2: Some Pellet reasoner inferred axioms result for Influences Model

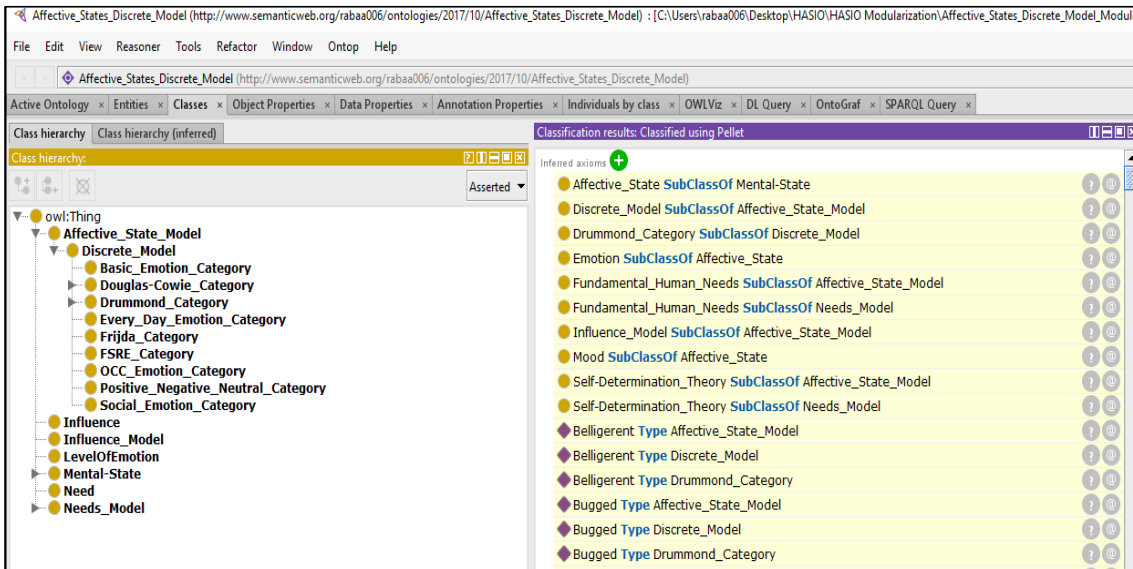


Figure 5.3: Some Pellet reasoner inferred axioms result for Affective Sates Discreet Model

Table 5.3: Pellet reasoner results on HASIO modules

Module Name	Asserted Axiom Count	Inferred Axiom Count
Influences Model	1293	1713
Influence Recognition	52	5
Affective States Recognition	1381	4
Affective States Influences Relations	724	7
Emotion Expression Cues	303	0
Affective States Causes Reaction	208	0
Affective States Dimensional Model	102	14
Affective States Appraisal Model	135	0
Affective States Discrete Model	1213	1371
Affectional	35184	35181

5.4 HASIO and HASIO Modules Accessibility

We used OnToology for publishing HASIO and its modules online. OnToology ⁴ is a system that automates part of the collaborative ontology development process. It reviews a given repository and produces diagrams, complete documentation and validation based on common pitfalls. OnToology supports OWL and RDFS vocabularies and used OOPS! for validation purposes. First, we created a repository for HASIO and HASIO modules in GitHub ^{5,6}, and then allowed OnToology to access these repositories.

In addition to validation in Section 5.1, we addressed the errors generated with OnToology; these errors from an important category in OOPS! missing domain and range, and missing disjoint. OnToology validates an ontology and produces issues that can be found in the GitHub repository. After we corrected these issues, we validated HASIO and HASIO modules through OnToology until no more issues were produced.

⁴<http://ontoology.linkeddata.es/>

⁵HASIO can be found under: <https://github.com/rana-othman/Huam-Affective-States-and-their-influences-Ontology-HASIO>

⁶HASIO Modules can be found under: <https://github.com/rana-othman/HASIO-Modularization>

5.5 Conclusion

This Chapter presented an evaluation of HASIO and its modules. Evaluating an ontology is a crucial step in ensuring the quality and correctness of an ontology. Furthermore, evaluating a large-scale ontology through modules ensures quality. We evaluated HASIO and its modules for verification and validation by using OOPS!, which also scanned for major pitfalls. Underacting the ontology requirements allowed us to experience and deal with pitfalls. The OOPS! Ontology Pitfall Scanner was able to call attention to minor as well as critical pitfalls that were missed during the design of the ontology, enabling us to perform the evaluation in an iterative manner. Consequently, we were able to fix the pitfalls after detection.

For validation purposes, we used the CQs and designed the natural language interface system. This allowed us to make sure that HASIO had enough axioms to accommodate all the CQs. We also made sure that HASIO had all correct information required. Moreover, the task-based application facilitated the extraction of information from HASIO while dealing with the complexity of the SPARQL query. Inferring new axioms added more strength to our ontology while also ensuring consistency for HASIO and its modules. Pellet, a built-in Protégé reasoner, was used for this purpose. Pellet is considered a complete and capable OWL-DL reasoner. By using OnTool-ogy we shared HASIO and its modules online. We also have more ways to maintain the quality of the ontology. Ontology evaluation is a continuous process that we can carry on during and after development. Indeed, it should be carried on with the extension of the ontology.

Chapter 6

Case study: sentiment analysis on Twitter

Although lexicon-based and machine-learning approaches have developed a strong reputation in the realm of sentiment analysis, there still exists a gap in the semantic understanding of textual content. Ontology has the ability to capture the semantic association between concepts and the relationships within contents. With such an ability, the requirements of manual annotation in machine-learning approaches can be resolved. As a result, the sentiment analysis community is moving toward an ontological approach to represent a common-sense knowledge base [149]. Fortunately, ontology-based sentiment analysis has proven to have a richer semantic representation than lexicons [149]. Also, it addresses the fact that a single message might contain different notions of the same aspect. Therefore, a more elaborate understanding of the sentimental content can be obtained. Contrary to ontology, machine learning approaches understand the sentiment of messages as a whole, without semantically dividing and analyzing the messages. In this thesis, we investigated the capability of the ontological approach against machine-learning algorithms for sentiment analysis on social media. We argue that the ontological approach could compete with machine-learning algorithms to capture a more comprehensive sentiment behaviour from sparse and informal textual contents in social media.

Micro-blogging services, such as Twitter, are rich sources for sentiment analysis and understanding user opinion and feedback. Opinion mining or Sentiment Analysis is a branch of text mining that intends to conclude the polarity of a textual sentence toward positive, negative, or neutral. Sentiment analysis aids in observing public needs, mood and behaviors. It also helps in many domains such as politics and movie sales, and measures customer satisfaction [149]. Sentiment analysis supports the exposing of attitudes that people hold toward a subject or entity. Analysis of structured and unstructured data plays a noteworthy role in decision-making, ranging from movie selection to determining our daily satisfaction needs [3].

In Section 6.1 we provide a background on sentiment analysis and related work . In Section 6.2 we present sentiment analysis process based on HASIO.

6.1 Sentiment Analysis Background and Related Work

Sentiment analysis can be performed on three levels [6]:

- Document level
- Sentence level
- Feature level

Document sentiment level aims to classify a textual review on a single topic, as expressing a positive, negative or neutral sentiment [126]. The sentence sentiment level classifies each sentence as expressing a positive, negative or neutral sentiment [6]. Feature sentiment level intentions help to find and aggregate sentiment on entity's aspect mentioned in a document. For example, in movie reviews, the movie itself is usually the entity, while all things related to that movie (e.g., characters, events, goal, etc.) are aspects of that movie[163].

6.1.1 Sentiment Analysis Approaches

Sentiment analysis can be done through many techniques, which can be divided into two approaches: non-ontology based and ontology based [149].

6.1.1.1 Non -Ontology Based Approach

Machine learning approach is a popular method of Twitter sentiment analysis. Machine-learning can have supervised or unsupervised approaches. The supervised approach requires training data and tested data. Machine-learning requires manual labelling of enormous sets of tweets, in order for each domain to reach an acceptable level of sentiment analysis. Moreover, it assigns a sentiment score for the sentence as a whole. Naive Bayes Classifier [130] and Bayesian Network [65] are some techniques used in supervised methods. Alternatively, the unsupervised method is used when it is hard to find labeled training data. K-means is an unsupervised machine learning technique [98].

The accurateness of the machine-learning approach is based on the representative collection of labeled training texts and selection of features. In addition, the classifier trained on texts in one domain does not work with other domains, in most cases [86].

Lexicon-based Approach is another method of sentiment analysis. It is divided into a dictionary-based approach and a corpus-based approach. These use statistical methods to find sentiment polarity. The dictionary-based approach is a collection of words with their positive, negative or neutral sentiment strength score. The corpus approach is based on statistical methods that determine sentiment polarity. It counts the frequency of a word's occurrence in a document.

6.1.1.2 Ontology Based Approach

An ontology has a rich, semantic representation because it captures the semantic association between concepts and relationship. Consequently, the sentiment analysis community is moving towards an ontological approach to represent common-sense knowledge bases [149]. Ontology can be designed as a domain knowledge and consequently, some words can have differing polarity based on domain and context. In addition, some domains have special words that can express sentiments [185].

An ontology can be developed to analyze sentiment in a specific domain.

The Ontology-based Sentiment Analysis Process for Social Media content (OSAPS) is proposed in [175] to identify the problem area relating to customer feedback on postal service delivery issues. It is also proposed to generate automated online replies for those issues. An ontology model is built from extracted data (tweets) and used to determine issues from negative sentiments with SentiStrength. The process comprises of data cleaning, extract-only combination of noun and verb tags for query-building, and retrieving information from SPARQL Query and ontology model.

A domain ontology for smartphones was created to analyze mobile tweets. The aim of the ontology is to accept tweets as input and to provide sentiment analysis in the domain. Therefore, the ontology consists of smartphone vocabulary. OpenDover's was used to assign a sentiment score for each tweet. OpenDover's is a web service that tags opinion and sentiment in a textual corpus that assigns a sentiment score [-10,10] [104].

An ontology for mobile product sentiment analysis was created in OWL format by retrieving vocabularies and data features from mobile and online shopping sites. For example: camera is a vocabulary and zoom capacity is a feature. The feature opinion score is obtained from the Stanford Natural Language Processor tool that ranges from [-2 to 2]. They built the SPARQL query interface to accept user queries and answer them with regard to a mobile product. For example, a possible query could be 'mobile with good battery life.' The system answers the user query based on stored features and opinion scores [132].

An ontology was created for sentiment analysis regarding electronic products. It contained a sentiment class with subclasses for emotion words (happiness and sadness) and electronic products.

These subclasses were extracted from an online customer reviews survey. HowNet dictionary was used to calculate the semantic similarity of words. As a result, the ontology is able to analyze a user query, such as 'Which tablet PC is excellent?' [156]

By contrast, ontology can serve to analyze sentiment in a general free domain. The Emotive Ontology [172] was built to detect and analyze emotions in informal text from social media. The approach detects a range of eight high-level emotions: anger, confusion, disgust, fear, happiness, sadness, shame and surprise. The Emotive Ontology is also capable of expressing the intensity of emotions. During the creation of the Emotive Ontology, many dictionaries and word datasets were examined, such as WordNet. Natural Language Processing (NLP) and part of speech tagging were used as pre-processing steps for emotion detection. The ontology was tested and evaluated on a dataset taken from Twitter. Even though the Emotive ontology [172] was created to capture emotions from textual content, its performance evaluation is limited for three reasons: 1) the dataset was small, containing only 150 tweets, 2) it was annotated by only two users, and 3) the tweet collection was event-related.

6.2 Sentiment Analysis Process Based on HASIO

As presented in Section 6.1.1.2 most existing domain sentiment ontologies were created based on emotional words related to domain-specific datasets. This results in a limitation when trying to adapt a domain ontology into various domains. We overcame this drawback by employing HASIO in sentiment analysis. As mentioned in Chapter 4, HASIO integrates emotion vocabularies from psychological theories, as well as from a wide range of lexicons and thesauri in order to ensure that a large set of emotion-related vocabulary was covered. Moreover, commonly encountered emotions within the collected data were added to the ontology. In Section 6.2.1 we introduce the tweet polarity calculation algorithm; HASIO sentiment analysis evaluation performance is outlined in Section 6.2.2. The results of our ontology-based sentiment analysis are compared with the machine-learning method in Section 6.2.3.1.

6.2.1 Tweet Polarity Calculation Algorithm

As Shown in Figure 6.1, we divided the tweet polarity calculation algorithm into three main stages: tweet pre-processing, tweet processing and tweet post-processing.

As illustrated in Figure 6.2, in the **tweet pre-processing** stage we prepared the twitter dataset by applying tokenization on the tweets using regular expressions. We took an extra step regarding

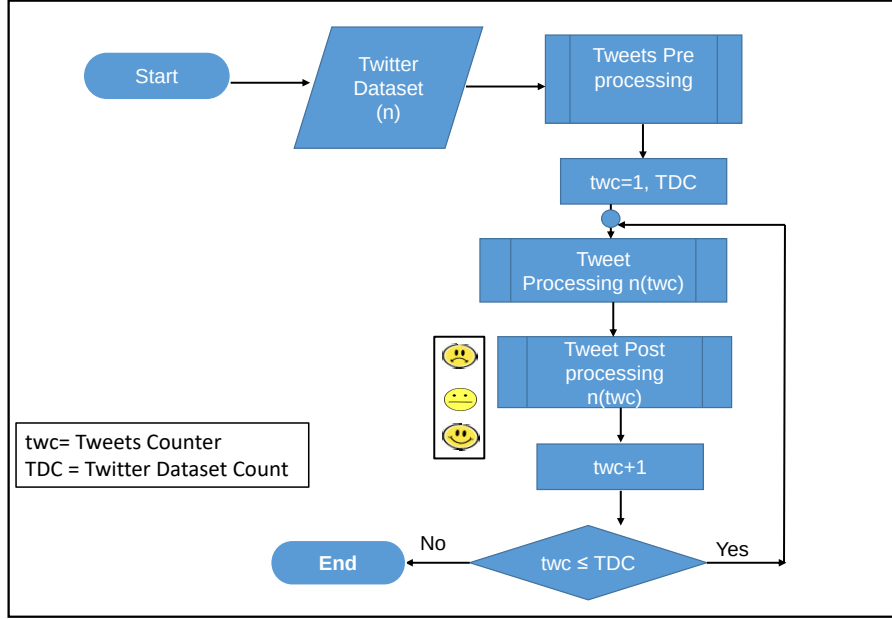


Figure 6.1: Tweet polarity calculation algorithm.

data preparation by converting any emojis into text. Since people frequently express their feelings by using emojis, these symbols have an important effect on the resulting sentiment [89]. We converted the emojis in the data to an equivalent word by using matching rules based on Emoji Sentiment Ranking ¹ and Home of Emoji Meaning ². In addition, spelling correction was applied to the text and we removed URLs, emails, user handles (@user) and punctuation using regular expression patterns.

Next, the aim of the **tweet processing** stage is calculating a Tweet Strength Score (TSS) where we applied sentiment analysis on a sentence level. For each tweet, we ran the SPARQL query to get the strength score for the tokens that affect overall sentence sentiment. We ignored the pronouns and articles in the sentence because they do not give an impression about emotion words. If the token did not have a match in the ontology, we ran the SPARQL query for the current token with the next token. We used the parameterized SPARQL query to apply a query against the ontology (HASIO) . We also used the Jena Java API ³, which is a Java framework

¹http://kt.ijs.si/data/Emoji_sentiment_ranking/

²<https://emojipedia.org/>

³<https://jena.apache.org/>

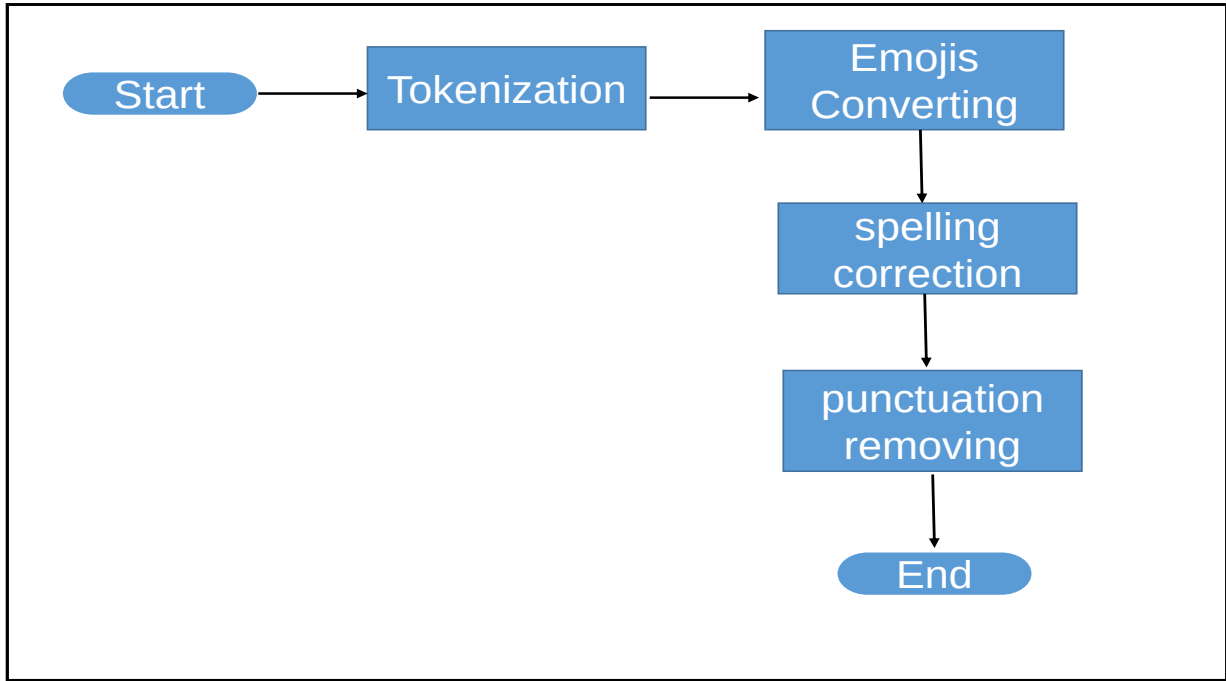


Figure 6.2: Twitter dataset pre-processing.

that provides support for manipulating and querying RDF models. As shown in Figure 6.3, and Figure 6.4, we generated a parameterized SPARQL query for each token to get the TSS from HASIO. Next, we send KSS to Tweet Strength Score Calculation unit.

The purpose of Tweet Strength Score Calculation unit is to store the highest positive token strength score in Positive Strength Score variable (PSS) and the lowest negative token strength score in Negative Strength Score variable (NSS). In HASIO, each individual belonging to **Positive Negative Neutral Category** subclass had a strength score between -5, and 5. In Tweet Strength Score Calculation unit , we checked if KSS had a positive or negative score. If positive, we replaced PSS value with KSS, if KSS was greater than PSS. Otherwise, if KSS had a negative score, we replaced the NSS value with KSS, if KSS was smaller than NSS. If KSS was equal to zero, the values of PSS and NSS would not be affected. After we extracted all the tweet token strength scores and concluded the values of PSS and NSS, we calculated the Tweet Strength Score (TSS) by adding the values of PSS and NSS. We followed the SentiStrength method to calculate the overall score of the sentence [176].

Finally as shown in Figure 6.5 , in the **tweet post processing** stage, we determined the tweet polarity (TP) based on the tweet strength score (TSS) from the tweet processing stage. If the TSS

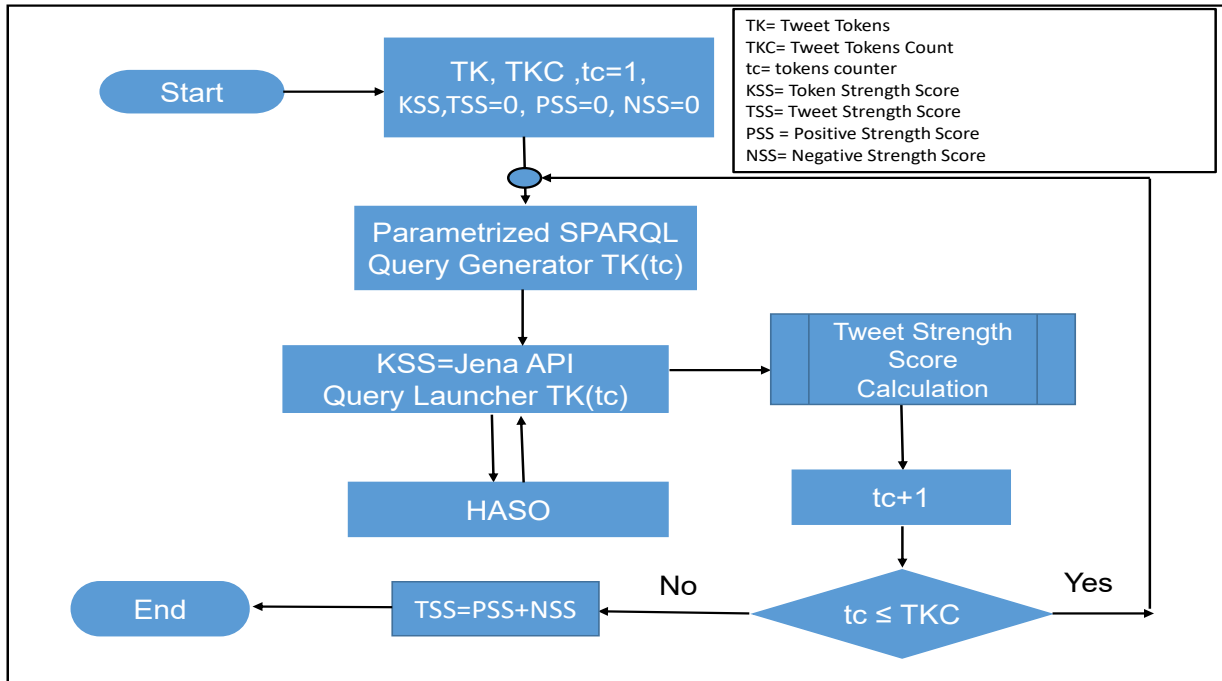


Figure 6.3: Tweet processing .

was larger than or equal to 1, then the TP is positive. If the TSS was less than or equal to -1, then the TP was negative. Otherwise, the TP was neutral.

6.2.2 HASIO Sentiment Analysis Evaluation Performance

After we employed HASIO on the dataset to classify the tweet sentiment analysis, we evaluated the result by calculating average recall (or average accuracy) and the average F score. Next, we compared the HASIO result with the machine-learning result. To do this, we used the following functions: `sklearn.metrics.recall`, `sklearn.metrics.accuracy_score`, and `sklearn.metrics.f1`. These were utilized to calculate the average recall, average accuracy, and average F score, respectively ⁴. These metrics belong to the free python machine learning library scikit-learn and can handle multilabel classification (positive, negative, and neutral).

⁴<http://scikit-learn.org/stable/modules/classes.html#module-sklearn.metrics>

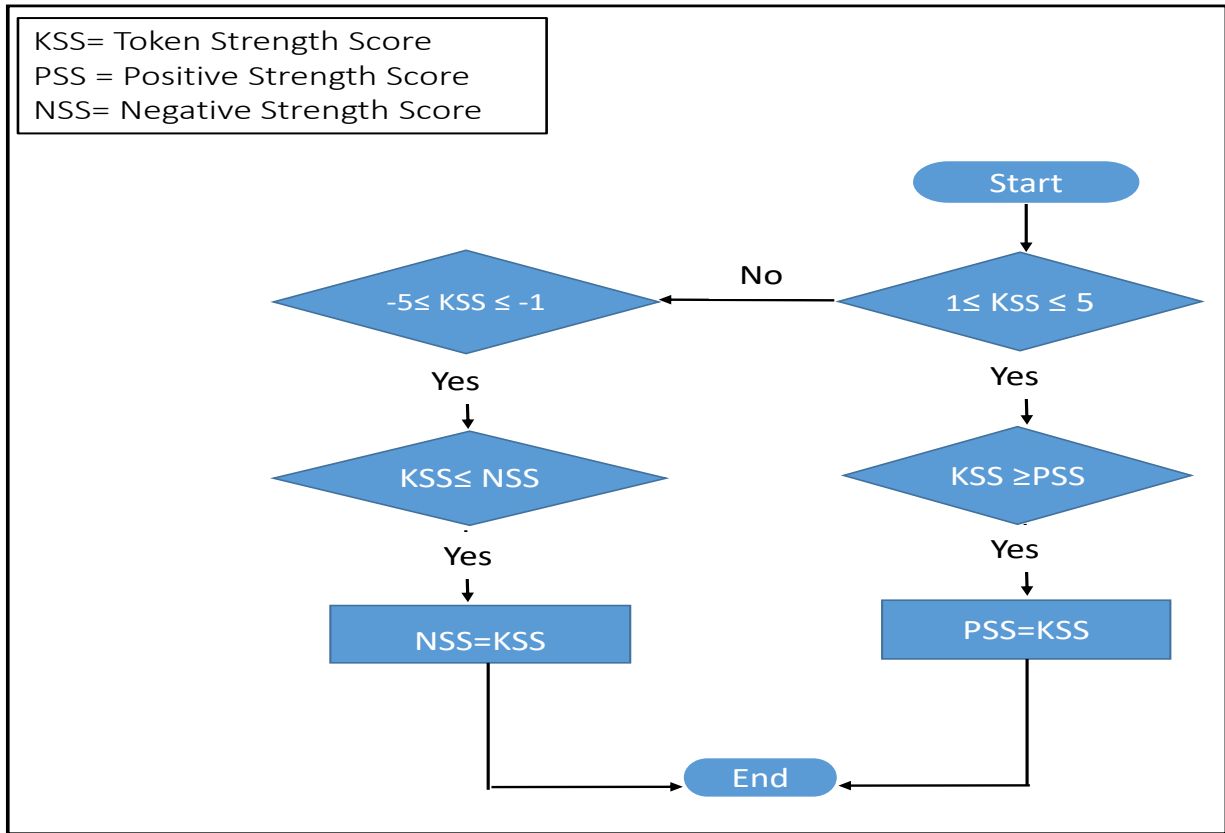


Figure 6.4: Tweet strength score calculation.

6.2.3 Applying HASIO For Sentiment Analysis on Available Dataset

In this section we demonstrate the effectiveness of HASIO in sentiment analysis by applying it in two different data sets. We also provide the HASIO sentiment analysis result and compare it with the machine learning approach result. In Section 6.2.3.1 we used HASIO for sentiment analysis on Domain-Free Sentiment Multimedia Dataset. In Section 6.2.3.2 we used HASIO for sentiment analysis on SemEval-2017 Task 4, subtask A Dataset.

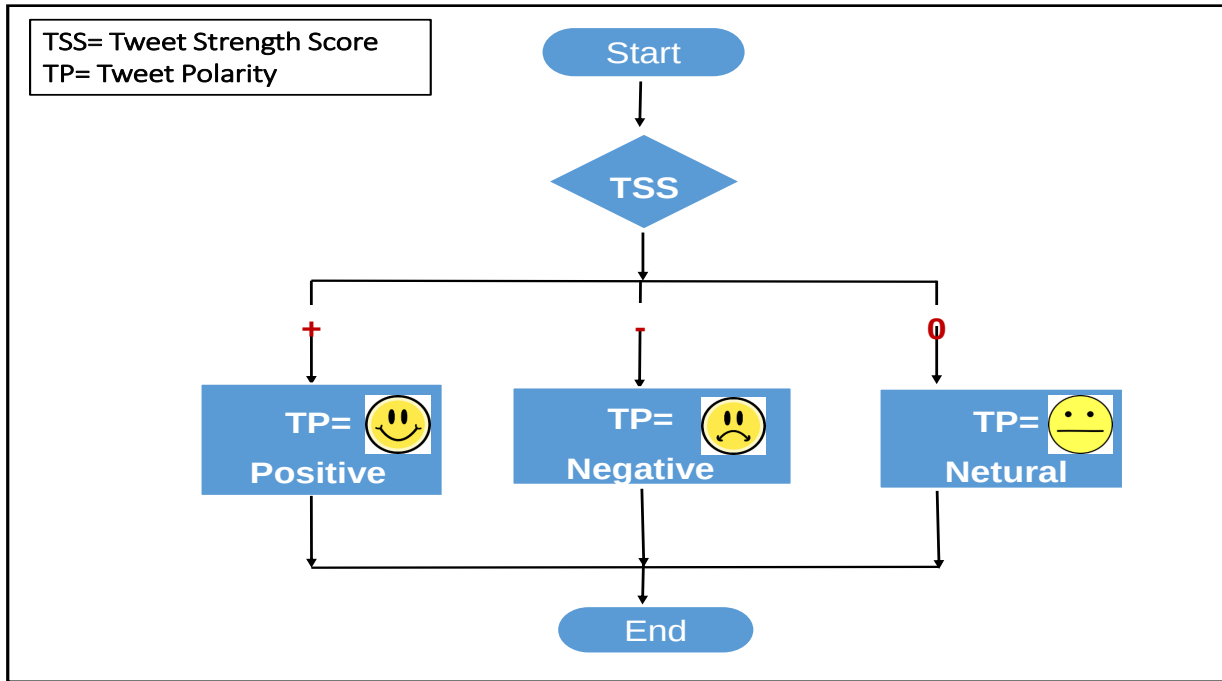


Figure 6.5: Tweet polarity determination.

6.2.3.1 Applying HASIO for Sentiment Analysis on Domain-Free Sentiment Multimedia Dataset

We applied HASIO Sentiment Analysis on Domain-Free Sentiment Multimedia Dataset (DF-SMD) ⁵. The dataset for DFSMD was collected from Twitter, while the fetching process was free of keywords in order to respect the purpose of creating a generalized dataset independent of topics and emotions. The tweets were collected worldwide from five different days, chosen randomly to ensure that many topics and events discussed daily were covered. The data was annotated manually with a positive, negative or neutral label. Table 6.1 shows some examples of tweet sentiment analysis results with HASIO on DFSMD. In the presented examples, we ran the SPARQL query for each word (token) to get the sentiment strength. The query result may return a positive number, a negative number, or zero based on how we present the word in the ontology. In some cases, the queried word may not be present in our ontology. Consequently, the SPARQL query result will be zero. In the column "Word Strength value by SPARQL Query" we presented words that affect the tweet's overall sentiment polarity. We ran the SPARQL query for each word in all of the tweets.

⁵www.mcrlab.net/datasets/dfsmd/

Table 6.1: Example of Tweets sentiment analysis result of HASIO on DFSMD

Sentence (Tweet)	Word Strength value by SPARQL Query	Tweet Sentiment Result
a very pleasant weekend it is pleasant real	HASIO :pleasant (3)	Positive
exam answer fails these are so funny	HASIO :fails(-3) HASIO:funny (2)	Negative
low quality selfie low quality person	HASIO :low (-2)	Negative

Table 6.2: Comparison of ontology and machine learning approaches for sentiment analysis on DFSMD

Method	Avg. Accuracy	Avg. F-score
HASIO (Ontology)	0.660	0.66
DFSMD (SVM)	0.647	0.64

The experimental results of the machine-learning mode (SVM) compared to the HASIO method is shown in Table 6.2.

6.2.3.2 Applying HASIO for Sentiment Analysis on SemEval-2017 Task 4,subtask A Dataset

SemEval-2017 Task 4 ⁶ consists of five subtasks; one of them is Subtask A: " Given a tweet, decide whether it expresses POSITIVE, NEGATIVE or NEUTRAL sentiment ". The dataset for Subtask A was general; the tweets were collected without specific keywords. The tweets' topics were diverse, such as movies, songs, singers and politics. There were 38 teams participating in Subtask A [154]

Table 6.3 shows some examples of tweet sentiment analysis results using HASIO. In the presented examples, we ran the SPARQL query for each word (token) to get the sentiment strength. The query result may return a positive number, a negative number, or zero based on how we

⁶<http://alt.qcri.org/semeval2017/task4/index.php?id=data-and-tools>

present the word in the ontology. In some cases, the queried word may not be present in our ontology. Consequently, the SPARQL query result will be zero. In the column "Word Strength value by SPARQL Query" we present the words that affect the tweet's overall sentiment polarity. We ran the SPARQL query for each word in all of the tweets.

Table 6.3: Example of tweets sentiment analysis result of HASIO on SemEval-2017 Task 4 sub-task A

Sentence (Tweet)	Word Strength value by SPARQL Query	Tweet Sentiment Result
I watched 25+ minutes of a Facebook live video hatching one of these and I regret every second	HASIO: regret (-2)	Negative
Entrepreneurship is about risk-taking, this time it is paying off	HASIO : risk-taking (3)	Positive
Hopefully Trump will designate as a terrorist organization and law enforcement can end reign of terror	HASIO: Hopefully (2) HASIO: terrorist(-3) HASIO: enforcement(-2)	Negative

In SemEval-2017 Task 4 Subtask A, participating teams were ranked according to their average recall (AvgRec) results, where a higher score is better. We compare our proposed ontology results with three of the top10 teams who used SVM method . Table 6.4 shows the comparison of the sentiment analysis results between our proposed ontology (HASIO) and three of the top 10 teams that participated in Subtask A [154]. The results in Table 6.4 show that our ontological method (HASIO) came in second, after the INGEOTEC team, with a small difference of 0.003 points in average recall.

Table 6.4: Comparison of ontology and machine learning approaches for sentiment analysis on SemEval-2017 Task 4 subtask A

System	Avg Rec	Avg. F-score
INGEOTEC	0.649	0.645
HASIO	0.646	0.637
SiTAKA	0.645	0.628
UCSC-NLP	0.642	0.624

Overall, our method came in 8th place after INGEOTEC, compared to all 38 participating teams, as shown in [154]. This demonstrates the effectiveness of the ontological method in the area of sentiment analysis.

Applying HASIO into the mentioned two datasets demonstrates the effectiveness of the ontological method in sentiment analysis, compared with the machine-learning method. HASIO is designed to cover a wide range of sentiment words from language dictionaries and psychological-based resources. With the ability of the ontology and performance in the sentiment analysis area, the requirements of manual annotation in machine-learning approaches can be resolved. Moreover, an ontology has the ability to represent domain vocabularies that can have different representation in another domain and context [35].

Sentiment analysis uses natural language processing to identify the human sentiment, incorporating more features from natural language processing may improve the overall ontology sentiment analysis result. In the future, we intend to experiment on our ontology with a combination of NLP features. Moreover, we intend to extend it with more language dictionaries and psychology-based resources, and to evaluate it with different datasets.

Chapter 7

Conclusions

Ontologies have been used in various domains to deliver a standard representation of the concepts and relationships within that domain. They are designed and developed based on their goals and the application's requirements. Using an ontology allowed us to model human affective states and their influences in a computerized manner.

Developing an ontology starts with determining the need and purpose for developing it. As a result, developers can ascertain the appropriate way to build an ontology and to consider resources of information. This is ongoing process where developers can represent greater domain knowledge and look for new informational resources. Ontology developers may face challenges, since there is no one way to develop an ontology. However, defining the purpose of developing an ontology and stating competency questions can ease and clarify the development process.

This thesis presents the conceptualization of an OWL vocabulary that describes the Human Affective States and their Influences domain along with its relationships. It begins with our motivation and the problem statement. Then we presented a background related to ontology and semantic web as well as the Human Affective States and their Influences from the psychology domain. Then, we surveyed existing ontologies related to the latter.

Furthermore, we presented the development of HASIO as it expresses concepts regarding human affective states and their influences, while also describing their inter-relationships. Consequently, HASIO is not just a simple taxonomy or a hierarchy of concepts, but it models psychological theories and emotional lexicons in a computerized format that can be used to develop human affective applications. In addition, we analyze resources from psychological theories, available lexicons and existing ontologies to configure the CQs that meet the purpose of HASIO development.

We also showed how it was modularized into separate modules that support reusability, scalability, evaluation and maintenance. Modularization aids in using subparts of the ontology in an different applications.

Indeed, ontology evaluation is a very crucial component in the ontology development process to insure correctness and quality. To show this with HASIO, we evaluated it through a web- based tool named OOPS!. Understanding the purpose and the requirements of the proposed ontology (HASIO) enabled us to realize and consider OOPS! Pitfalls and correct them. In addition, we evaluated HASIO through a Question Answering system (HASIOQA), a task- based evaluation system. We designed and developed a natural language interface system for this purpose. Besides validation purposes, it serves as a catalogue for HASIO that facilitates queries with natural language, rather than using a SPARQL query.

Additionally, we used OnToology tool to ensure the quality and correctness of the module. Employing HASIO in Sentiment analysis areas demonstrates the effectiveness of the ontological method compared to the machine learning technique. We designed and developed a tweet polarity calculation algorithm for this purpose. Ontology allows an easy way to represent and share knowledge about positive, negative and neutral terms for Sentiment analysis systems and applications.

In the future, we plan to employ HASIO in detecting human needs satisfaction from social media. We would like to use and benefit from the relationship between emotion and need. Since emotions are generated by needs they can therefore serve as a guide to identify the state of satisfaction of a person's needs. Human need satisfaction reflects the expressed emotion [8].

Moreover, we can integrate HASIO to determine human personality types. HASIO models the Big Five personality theory with the adjectives for each personality type. Type can be measured by using various principles, such as linguistic features, type of follower and following [146]. Therefore, this part of the ontology can be a sub-component of a system that detects an individual's personality type in order to serve the person better in different domains, such as music selection or food recommendation.

Human mood can be used as a way to recommend many life aspect, such as music [9]. In our proposed ontology, we represent the mood models. Consequently, HASIO can be used to detect and analyze human mood in the textual realm, such as social media. As a result, HASIO can be a component in a recommender system.

Since Subjective well-being plays an important role in displaying life satisfaction, detecting it in social media is beneficial. Incorporate Word Count (LIWC) ¹in HASIO will help us in this

¹<https://liwc.wpengine.com/>

mission. LIWC is one of the most popular dictionaries in SWB research [113]], as it contains more than 6,000 words. Detecting SWB can aid to understand a person's emotions and mood.

As we presented in HASIO, both emotion and mood are influenced by SWB. Employing HASIO SWRL powers the ontology with decidability in top of knowledge representation. OWL and SWRL opens an opportunity to use HASIO as a recommendation system. For instance, SWRL can facilitate the determination of a person's emotion based on the causes. As a result, the system can recommend a way for the person to deal the causes.

Another great application of combining HASIO with SWRL is determining a person's expected SWB based on their personality. In HASIO, we present the relationship between SWB and personality. Moreover, we can add SWRL when discovering a person's expected emotion based on their personality. This could work with an application that helps a teacher identify their students' emotions based on their personalities. As result, a teacher can deal with each student in a personalized way.

It is an interesting idea to employ HASIO in a multi-agent system that is responsible for detecting and analyzing human affective states. In a multi-agent system environment, subagents have to collect data and analyze them, which requires that subagents interact with each other . Employing HASIO in such a system would unify all the subagent semantic points of view. This causes all the subagents to communicate easily and correctly [84]. Multi-agent systems are beneficial for a smart city scenario, where multiple systems observe and collect data about citizens while other systems analyze the data. HASIO can be extended to model and represent the smart city real world model , so we can employ HASIO in smart cities.

Additionally, in the future we want to extend HASIO by incorporating more emotion dictionaries from different languages. This will cause opportunities to use HASIO in affective state analysis in languages other than English. NRC Emotion Lexicon² has emotion lexicons in languages such as Arabic, French and Chinese. Mapping between emotion terms from different languages may be a challenge because some terms in one language may not have an equivalent term in another. Collaboration with language experts in this regard will enhance the quality of HASIO.

HASIO can be used to detect emotion from facial expressions; however, cultural aspect has to be taken into consideration. Some emotions have the same facial expressions across different cultures while others are expressed differently. As a result, we need to extend HASIO to model emotion facial expressions of more cultures [5].

This thesis aims to provide a shared and interoperable vocabulary that allows for computer systems to better understand and conceptualize Human Affective States and their Influences. Therefore, In this thesis we did the following:

²<http://www.saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm>

- Survey and analyzing the existing ontologies regarding human affective states and their influences.
- Develop Human Affective States and their Influences Ontology (HASIO)
- Analyzing the resources from psychology theories, available lexicons and existing ontologies to configure HASIO CQs
- Modularize HASIO into modules.
- Design and development :
 - HASIO Natural Language Interface System
 - Tweet polarity calculation algorithm to employ HASIO into sentiment analysis

HASIO can be extended and kept up-to-date according to new psychological studies and findings. This can be accomplished by adding more classes, sub-classes, or even relationships; more CQs may also be needed as the evaluation carries on. Representing more knowledge in HASIO can strengthen the purpose and use of HASIO natural language interface system. A user can gain more information in human affective states and their influences in an easy and pleasant approach.

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APPENDICES

Appendix A

HASIO and its modules Screenshot

The screenshot displays the HASIO web application interface. At the top, there is a navigation bar with tabs for 'Active Ontology', 'Entities', 'Classes', 'Object Properties', 'Data Properties', 'Individuals by class', 'DL Query', 'Individual Hierarchy Tab', 'SWRLTab', 'VOWL', and 'SPARQL Query'. Below this, the 'Ontology metrics' tab is selected, showing a table of metrics. The 'Ontology header' section below the table provides metadata about the ontology, including its IRI, version IRI, name, location, creator, language, engineering tool, syntax, and type.

Ontology metrics:	
Metrics	
Axiom	77831
Logical axiom count	57934
Declaration axioms count	19191
Class count	276
Object property count	106
Data property count	105
Individual count	18691
Annotation Property count	20
DL expressivity	ALCROL...
Class axioms	
Ontology header:	
Ontology IRI	http://www.semanticweb.org/rabaa006/ontologies/2014/4/HASIO
Ontology Version IRI	e.g. http://www.semanticweb.org/rabaa006/ontologies/2014/4/HASIO/1.0.0
Annotations	
rdfs:comment [language: uottawa.ca] The Ontology Metadata is Based on Ontology Metadata Vocabulary (OMV) http://mayor2.dia.fi.upm.es/ceg-upm/files/omv/OMV.owl Ontology Name: Human Affective States and their influences Ontology(HASIO) Location : Canada , Ottawa , the University of Ottawa Created By : Rana Abaali-hail , rabaa006@uottawa.ca Ontology Language : OWL Ontology Engineering Tool: Protégé Ontology Syntax : rdf:xml Syntax Ontology Type: Domain Ontology	

Figure A.1: HASIO metrics and header.

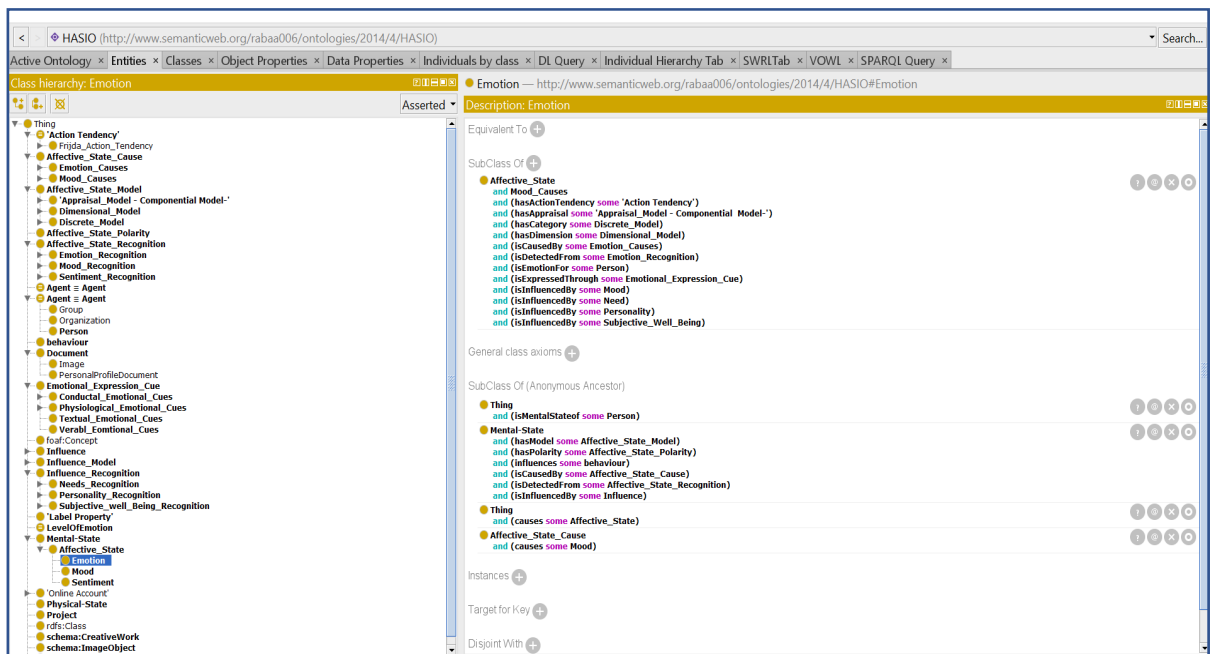


Figure A.2: HASIO class-subclass.

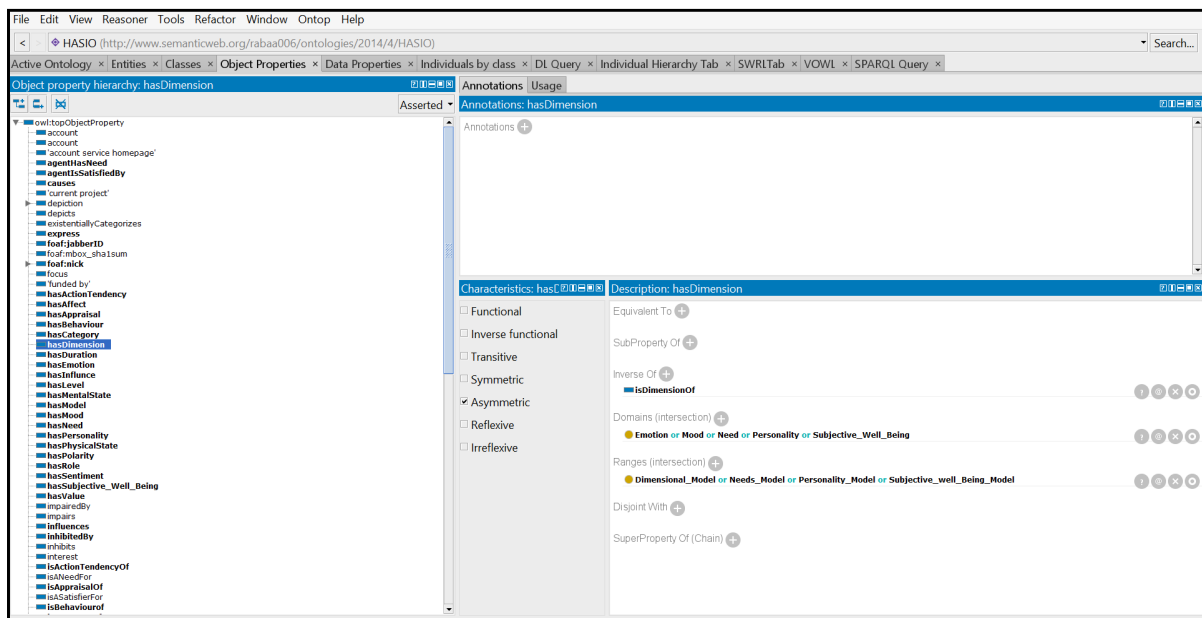


Figure A.3: HASIO Object Properties.

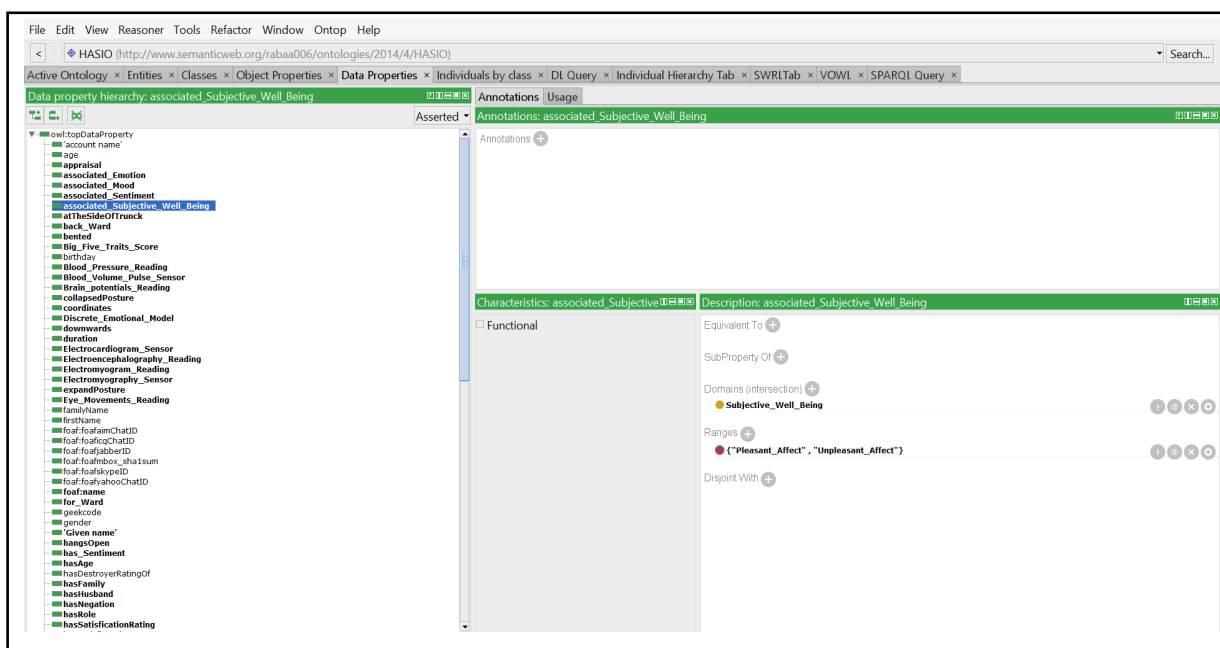


Figure A.4: HASIO Data Properties.

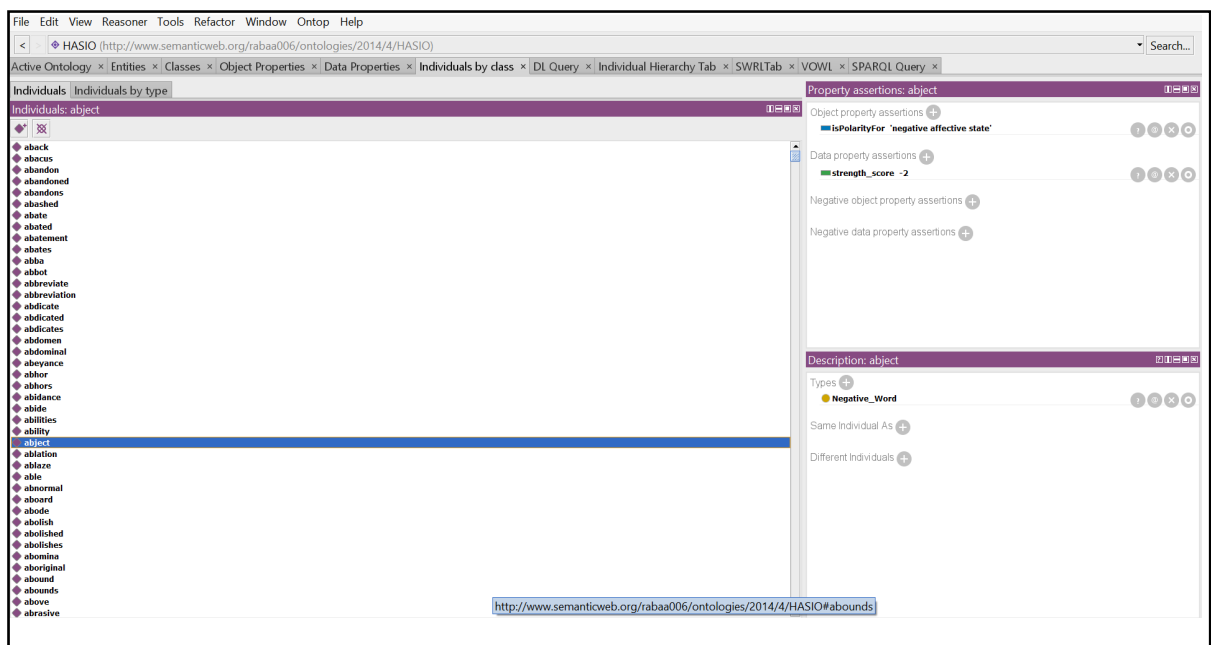


Figure A.5: HASIO Individual Type.

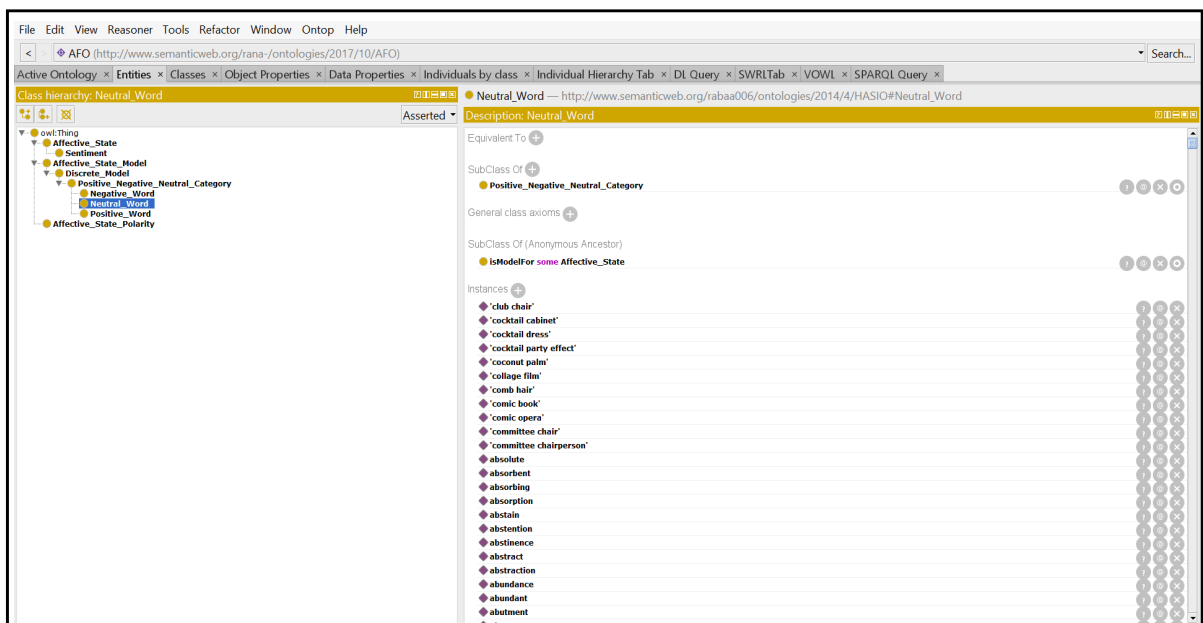


Figure A.6: Affectional Module.

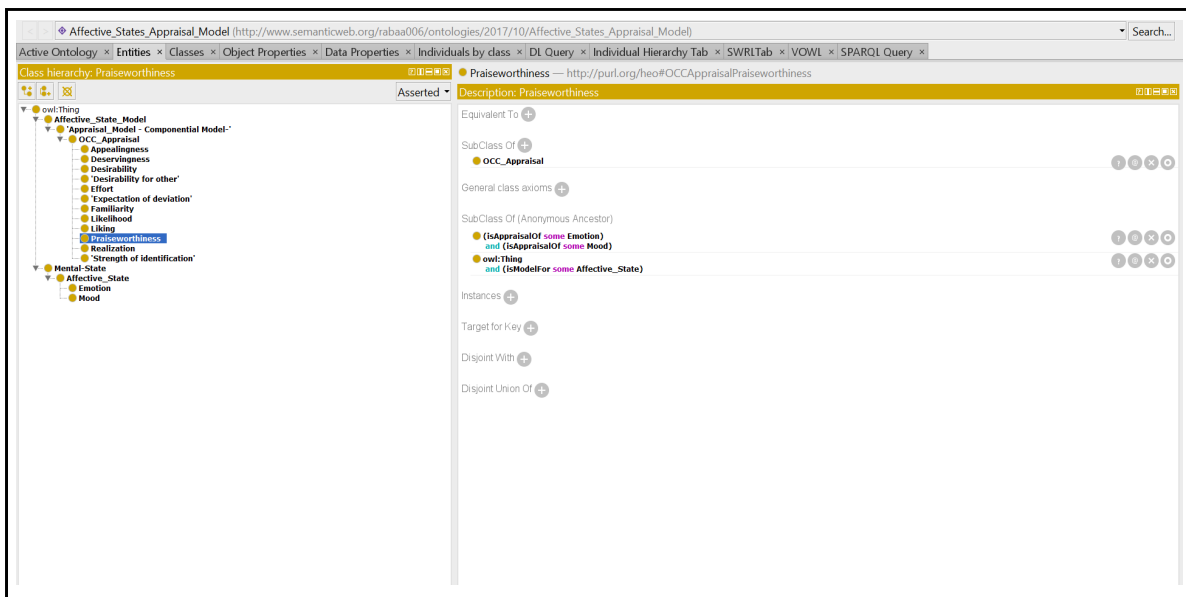


Figure A.7: Affective States Appraisal Model Module.

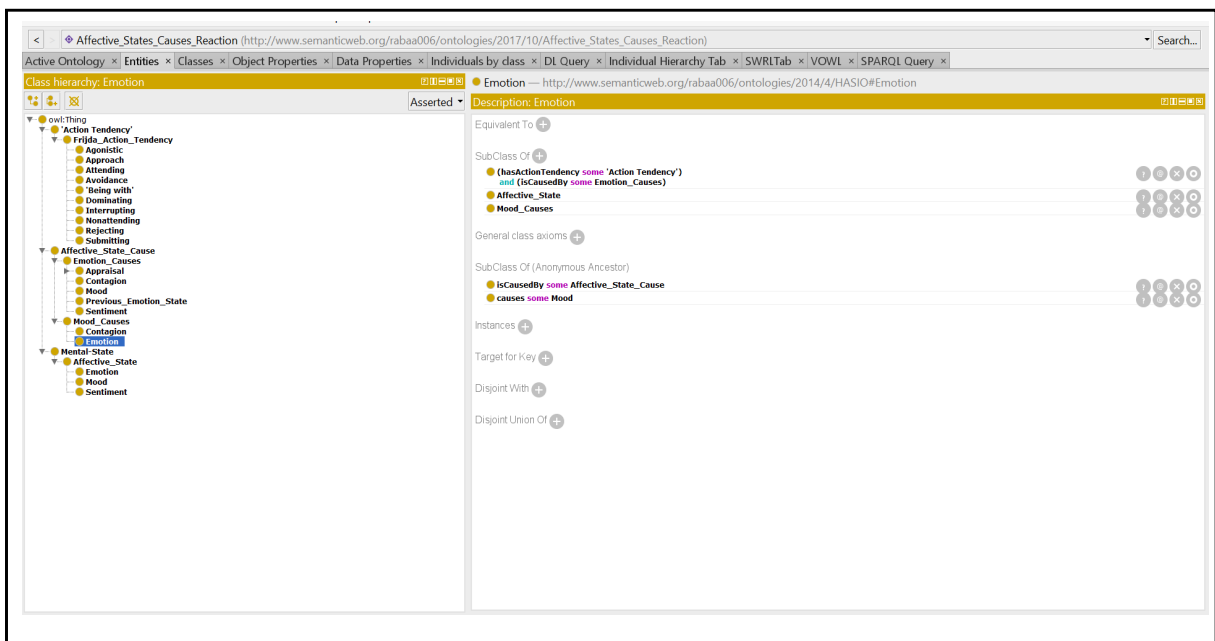


Figure A.8: Affective States Causes Reaction Module.

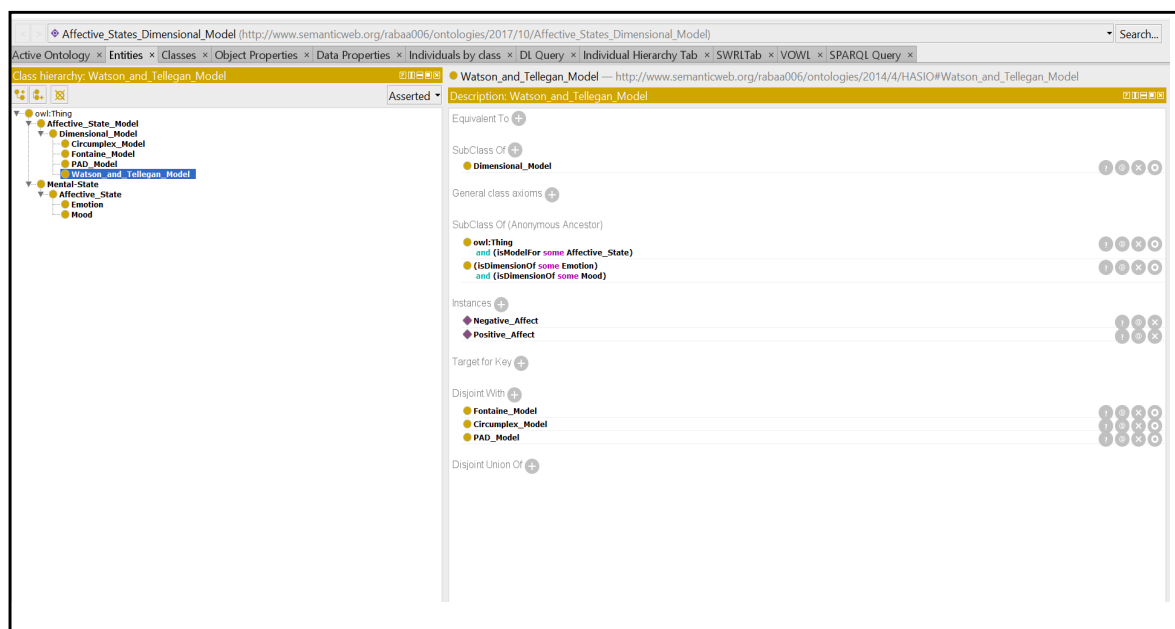


Figure A.9: Affective States Dimensional Model Module.

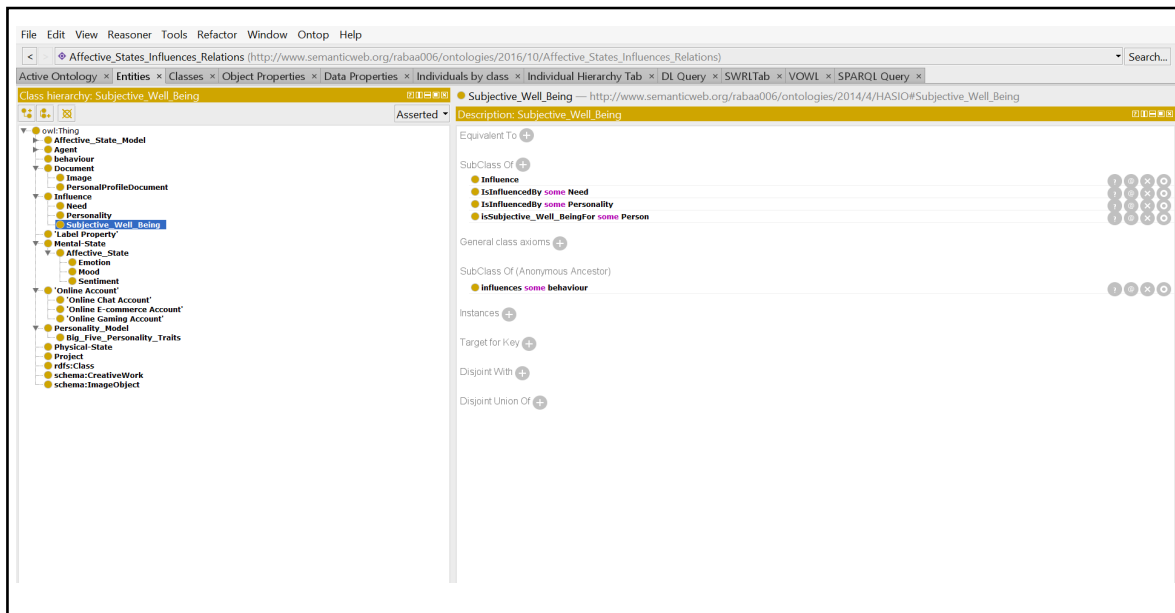


Figure A.10: Affective States Influences Relations Modules .

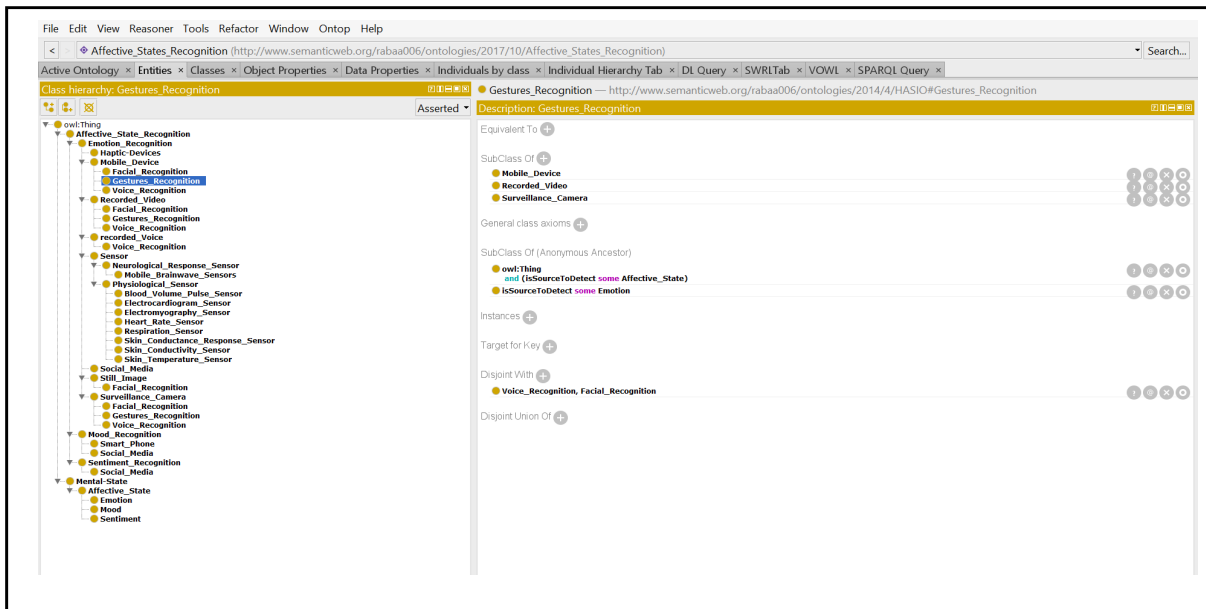


Figure A.11: Affective States Recognition Module.

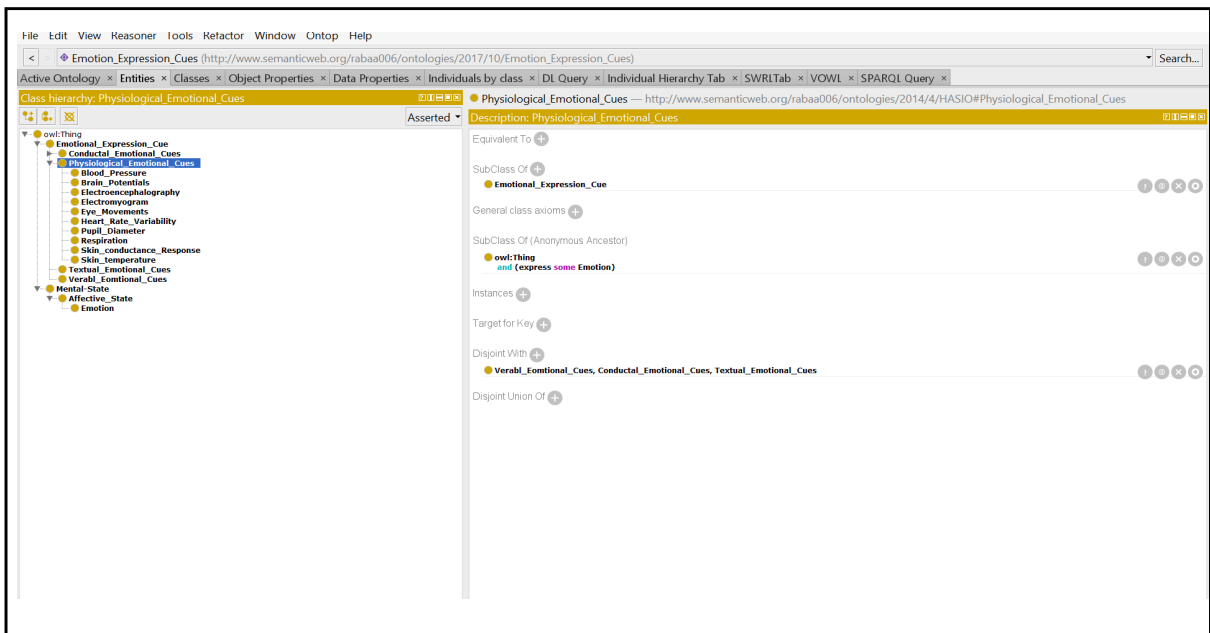


Figure A.12: Emotion Expression Cues Module.

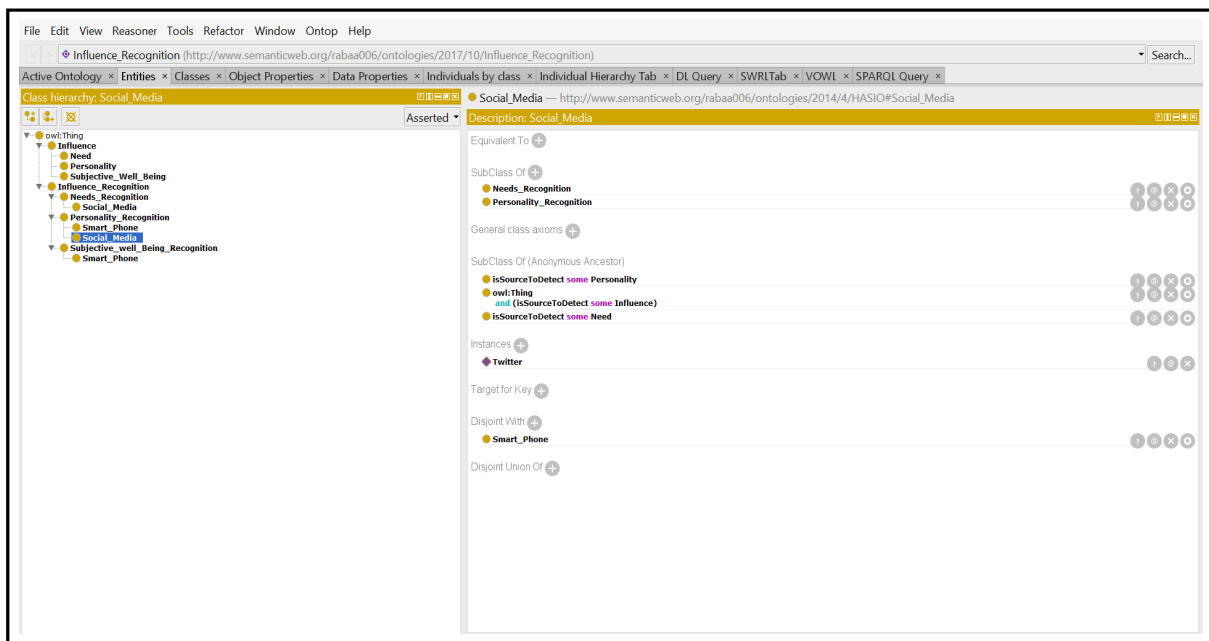


Figure A.13: Influence Recognition Module.

