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## Theme

# Developing an Ontology based context-aware system for citation recommendation purposes


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# ملخص

إن التزايد المستمر في عدد المنشورات العلمية التي يتم نشرها عبر الإنترنت تجعل من عملية البحث صعبة على الباحثين والمجتمع الأكاديمي للعثور على الأوراق العلمية الأكثر صلة بأبحاثهم. علاوة على ذلك ، يصبح الأمر أكثر تعقيدًا بالنسبة لهم لمواكبة أحدث الدراسات الحالية في مجالات أبحاثهم. ومن هنا تأتي الحاجة الى استغلال نضم التوصيات التي تعتبر أحد التقنيات الحديثة التي تزود المستخدمين بتوصيات ذات طابع شخصي والتي قد تكون من اهتماماتهم .على الرغم من وجود ابحاث سابقة في توصية الاستشهاد الواعية بالسياق نلاحظ نقص الدراسات التي تعتمد على نظام الأنطولوجيا .نقترح في هذا العمل أداة توصية تساعد على ايجاد الأوراق العلمية ذات الصلة تعتمد على خوارزمية التصفية الذكية مستندة في ذلك على الأنطولوجي الذي تم تصميمه ليتناسب مع مجال البحث العلمي .نقوم بانشاء واجهة مستخدم تساعد الباحثين للوصول الى الأوراق العلمية ذات الصلة بأبحاثهم.

**الكلمات المفتاحية :** نظم التوصية ،أنطولوجي ، واعي بالسياق

# ABSTRACT

The ever-increasing number of scientific publications online makes it difficult for researchers and the academic community to find the most relevant scientific articles. Moreover, it becomes more complicated for them to keep up with the latest studies in their research areas. Hence the need to exploit recommender systems which are a modern technology that provides users with recommendations of a personal nature that may be of interest to them. Although there has been previous research in context-aware citation recommendation, we note the absence of studies based on ontology system. In this work, we suggest a recommendation tool that helps find relevant scientific articles depending on an intelligent ontology-based filtering algorithm that is designed to fit in the scientific research domain.We create a user interface that helps researchers access scientific articles relevant to their research.

**Key words:** Recommendation system ,Ontology, context-aware

# RÉSUMÉ

Le nombre sans cesse croissant de publications scientifiques en ligne rend le processus de recherche difficile pour les chercheurs et la communauté universitaire à trouver les articles scientifiques les plus pertinents. De plus, il devient plus compliqué pour eux de se tenir au courant des dernières études dans leurs domaines de recherche. D'où la nécessité d'exploiter systémes de recommandations qui sont une technologie moderne qui fournit aux utilisateurs des recommandations d'une nature personnelle qui peut être d'intérêt pour eux. Bien qu'il y ait eu des recherches antérieures dans la recommandation de citation consciente du contexte, nous remarquons l'absence d'études fondées sur le système d'ontologie. Dans ce travail, nous suggérons un outil de recommandation qui aide à trouver des articles scientifiques pertinents dépend dant à un algorithme de filtre intelligent basés sur l'ontologie qui est conçu pour s'adapter dans le domaine de la recherche scientifique.Nous créons une interface utilisateur qui aide les chercheurs à accéder aux articles scientifiques pertinents à leur recherche.

**Mots clés:** Systèmes de recommandation, Ontologie , consciente du contexte

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# *Dédicacions*

## *My dear mother*

*The most precious person to me , who always supported me and took are of me when I was down and nearly giving up ,thanks mom for being by my side and hope you will live long and keep blessing me with your kindness.*

## *My father*

*The person who always got my back and pushed me to go futher he always pushed me to not giving up and made sure that i never needed anything my whole life thanks a lot dad for being by my side and i pray Allah to keep you safe and healthy as long as you live.*

## *My sisters and brother*

*Fatima, Amel, Khalida, Hadjer, and Lamine the greatest gift my parents gave me and a true blessing from God thanks for keeping me laughing and loving me all this years.*

## *My friends*

*Thanks for all the time we spent together and all the fun we had you guys took away the stress and pain of this journey, much love and much appreciation !!*

*LARABE Oumelkhir Ahlem*

# *Dédicacions*

*I dedicate this modest work first to God who gave me strength and vitality so that I could achieve my dreams of this diploma.*

*Yes to the first person whom his name was pronounced and who has always been at my side with his soul, his efforts and his prayers it is my dear mother, she is the light of my life,who encouraged me in every stage of my life and participates with me in the accomplishment of this work and to my dear father rahimaho Allah.*

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*To my husband Fedoul Nacer and my children Rodina and Abderrahmane.*

*To my brothers Aissa and Boudjemaa and Abderazzak and Abdraouf,*

*Soul mates lamia and zahra,*

*To all my husband's family*

*To my friends Ahlem,Amina,Hadjer,Kaouthar,Iman,*

*To the Souls teaching first juice that at university and its forget the students of the section of master computer science*

*SARA CHATOUH*

# LIST OF ABBREVIATIONS

**RSs** *Recommendation Systems*

**CBRS** *Content-Based Recommendation Systems*

**CFRS** *Collaborative Filtering Recommendation Systems*

**HBRS** *Hybride Fitering Recommendation Systems*

**OWL** *Ontology Web Language*

**Onto-RS** *Ontology Research Scientific*

**MASSPR** *Multi-Agent System Scientific Paper Recommendation*

# INTRODUCTION

In recent years, The rapid increase in online scientific publications makes research difficult for researchers and the academic community to find the papers most relevant to their research.

The search process for relevant articles to the use of scientific search engines is a time-consuming task. The researcher reads the title of the article and the summary to determine whether the article is suitable for reading and interesting or travels to search for other relevant articles for his research project.

Recommender Systems (RSs) have attracted attention because they aim to suggest items of potential interest for solving information overload after successfully applying them in many fields [9]. Paper recommender systems have also made finding information easier by recommending relevant scholarly publications [10].

But the majority of existing approaches to recommender systems Concentrate on recommending the most relevant products to specific consumers while ignoring other factors. Consider any contextual information ( namely users' context, document's context, and environment context) [11]. In other words, traditionally, When making suggestions, recommender systems deal with applications with only two sorts of entities: people and objects, and they don't place them in context. Paper recommender systems have also been used to make the effort of finding information easier by recommending appropriate scholarly publications based on more detailed information than a few keywords.

Moreover, Because of considerable efforts to standardize the semantic web or to the increasing use of associated data, there is growing interest in knowledge enhanced recommendation methods based on an Ontology model, which in turn provides semantic explanations of the concepts that belong to the elements of the recommendation area and their relationship with each other, as well as the possible application of internally built evidence techniques [12]. And thus, the possibility of designing intelligent advanced algorithms that take into account the meaning and connotations of the elements, can understand and explain the interests and preferences of users in the context of the application field and thus the possibility of generating recommendations of high accuracy and quality and establishing greater trust in the advising system by its users.

In this document, We propose an intelligent filtering mechanism called MASSPR (Multi-Agent System Scientific Paper Recommendation) that is based on ontology proposed Onto_RS (Ontology Research Scientific) that is building a graph of nodes contains from words and articles which are linked with each by a relationship that helps us to compute the word node pawer that will be used to compute the article node power in order to recommend relevant papers a tool that helps to deal with daily researchers challenge .

This thesis includes three chapters :

- **Chapter 1**, We start with the definition of recommendation system their different types, techniques and the context in recommendation system then the explanation of the ontology, its basic components,its classification and Ontology Web Language.
- **Chapter 2**, We mention the most famous related works and what have been suggested by researchers and writers in this field.
- **Chapter 3**, we present the implementation of the tool and the ontology proposed for recommendation system with an explanation of its most important contents,a brief explanation of the software used , finally a discussion of the result. a discussion of the results reported by each model.
- **And at the end**, We summarize what is mentioned before .

# CHAPTER 1
# BACKGROUND

## 1.1 Introduction

We divide this chapter into three parts. In Part I, we introduce recommender systems that have become ubiquitous in recent years in many domains. These systems are designed to help users find resources that interest them and are tailored to their preferences, among the large number of choices available to them. We deal with the recommendation systems so that we first define these systems and then review in detail the different types of them and the techniques used in them while mentioning. In the second part, we address the context and concept of context awareness, and its importance in joining and incorporating the recommendation. At the end we explain the ontology and then its basic components while mentioning its most important classifications.

## 1.2 Recommendation System

### 1.2.1 History

The ability of computers to make recommendations to users was recognized fairly early in the history of computing. Grundy [13], a library system, was a first step towards automatic recommendation systems. This system was quite primitive. It classified users into "stereotypes" based on a short interview, and used these stereotypes to produce book recommendations.This work was an interesting first attempt in the field of recommender systems. However, its use remained very limited.

In the early 1990s, collaborative filtering appeared as a solution to information overload. The year 1992 saw the appearance of the Tapestry document recommendation system [14], as well as the creation of the GroupLens research laboratory, which worked explicitly on the problem of automatic recommendation in the context of Usenet news forums. Tapestry's goal was to recommend to groups of users documents from the newsgroups that might interest them. The approach used was "nearest neighbor" based on the user's history. This is referred to as manual collaborative filtering, as a response to the need for tools for filtering information expressed at the same time. The recommendation results from a collaborative action of users who recommend documents to other users by giving them interest ratings according to certain criteria.Automatic collaborative filtering systems then appear. GroupLens [15] uses this technique to identify Usenet articles that may be of interest to a given user. Users need only assign ratings or perform other observable operations (e.g., read an article); the system then combines this data with the ratings or actions of other users to provide personalized results. With these systems, users have no direct knowledge of the opinions of other users, nor of the items in the system.

In recent years, recommender systems have become a subject of increasing interest in the fields of human-computer interaction, machine learning and information retrieval. In 1995, Ringo [16], a music recommendation system, based on user ratings, and Bellcore [17]. The same year, GroupLens created the company Net Perceptions whose first customer was Amazon. Nowadays, recommendation systems have become essential components for most e-commerce sites.

### 1.2.2 Definition

Recommendation systems are defined [9] as software tools that are tasked with providing each user with recommendations about the appropriate elements for them in processes that need to make good decisions (such as what elements can be purchased..) This allows the user to undertake a complex analysis of many of the options available and these recommendations are presented as a ranked list so that the elements in the first list are the most important and relevant to the user's preference.

In general, two basic types of recommendation systems are distinguished in terms of the specificity of recommendations made to users:

- **Non-personalized** It is a non-personal system if it does not rely on user information (user development) and therefore the systems do not distinguish users as independent individuals and generally secure the same recommendations for different users.

- **Personalized** Contrary to previous systems, personal recommendation systems rely on users' information collected and represented within the user model that includes their interests and preferences in order to make the recommendations proposed individually and independently.

### 1.2.3 Classification of recommender systems

For a system to deliver appropriate and relevant recommendations to its users, it is critical to deploy efficient and accurate recommendation mechanisms. This emphasizes the need to comprehend the characteristics and potentials of various recommendation approaches. The anatomy of several recommendation filtering techniques is seen in Figure 1.1 [1].

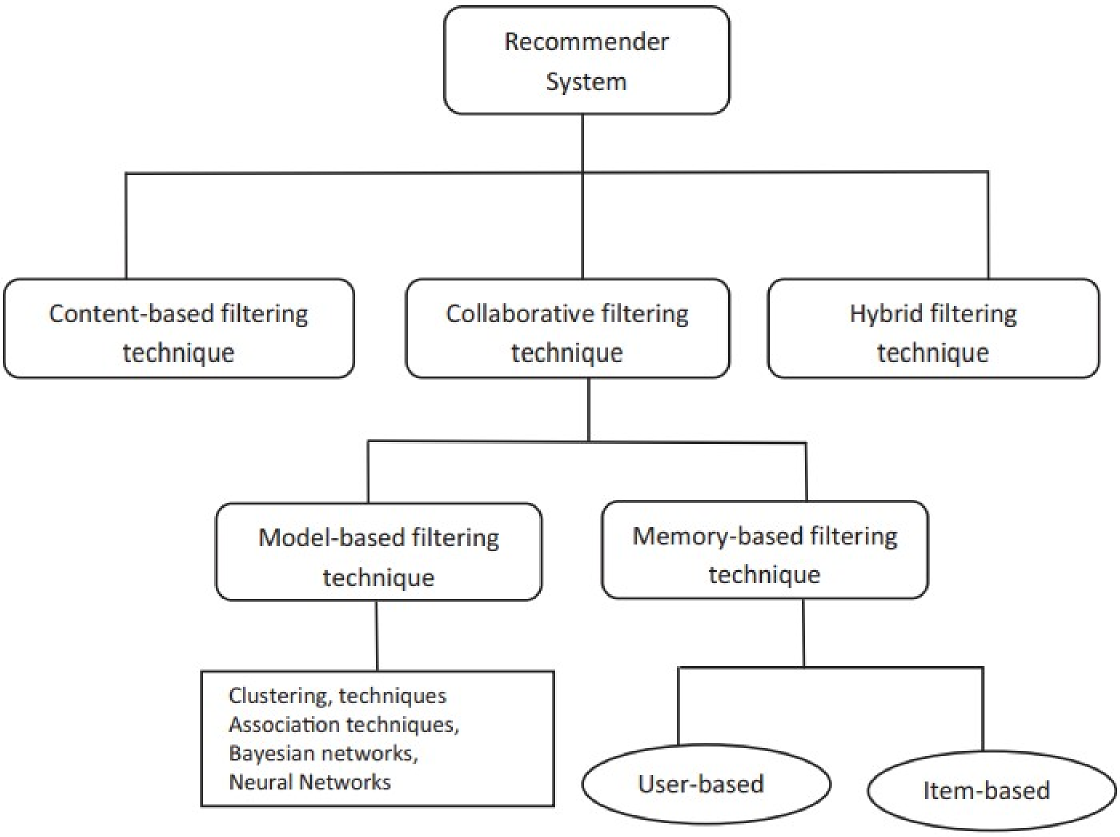



Figure 1.1: Recommendation Technique [1]

### Content-based recommendation recommendation systems

Content-based recommendation systems [18] attempt to recommend elements similar to those previously liked by the user. These systems analyze the explanations of the items assessed by the user by deleting the most important characteristics of the recommendation area that are subsequently used for the process of building user interest models and preferences. The content-based recommendation process, therefore, consists mainly of a process that corresponds the characteristics of the user model to those of the component by deleting a value that represents the level of the user's interest in that element.

### Basic structure of content-based systems

A content-based recommender system needs techniques to produce an efficient representation of the items and of the user's profile to be able to compare them. Thus [19] propose a high-level architecture (Figure 1.2) in which the recommendation process is performed in three steps, each one managed by a specific component:

- **Content Analyzer** When the information is not structured (for example, an item represented by a text), this module aims to carry out the pre-processing to extract the relevant information, structure it and represent it in an appropriate target form (for example a keyword vector).

- **Profile Learner** This module collects data representative of the user's preferences and generalizes this data to learn and build the user's profile. Machine learning techniques [20] can be used for this. Examples include decision trees, neural networks, and naive Bayes classification. These techniques aim to infer a profile of the user using information about the items they liked or disliked.

- **Filtering Component** This module filters the relevant items by matching the user profile representation to the candidate items for recommendation. The relevance of the item is calculated using similarity metrics between the item and the user profile. The greater the similarity with the "positive" profile and the smaller the similarity with the "negative" profile, the more likely the item is to be recommended.

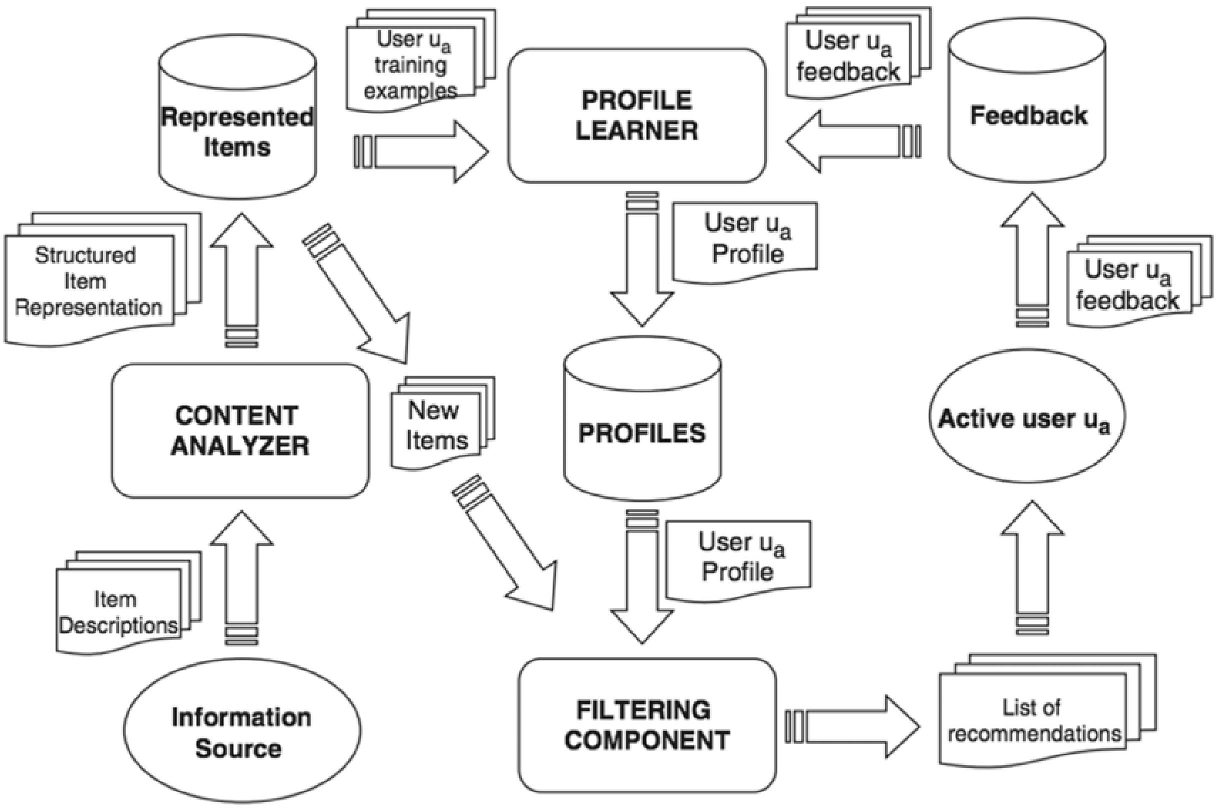



Figure 1.2: An architecture of a content-based recommendation system [2]

### User modeling in content-based recommendation systems:

One of the most widely used classification algorithms in our user modeling process

- **Naive Bayes** This method generates a probability model based on previously observed user history data. This classification is one of the most successful algorithms for classifying text content and has been used to model users' preferences in several content-based recommendation systems such as [21].

  The posterior probability is calculated by updating the prior probability by using Bayes' theorem,In statistical terms, the posterior probability is the probability of event A occurring given that event B has occurred.

  If A and B are two events in sample space S , then the Conditional Probability of A given B is defined as :

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)}, \text{ when } P(B) > 0 \tag{1.1}$$

  P(A) = The probability of A occuring

  P(B) = The probability of B occuring

  $P(A \mid B)$ = The probability of A given B

  $P(A \cap B)$ = The probability of both A and B occuring

  where is the joint probability of both A and B being true. Because

$$\mathrm{P(B \cap A) = P(A \cap B)}$$

$$\Rightarrow \mathrm{P(A \cap B) = P(A \mid B)P(B) = P(B \mid A)P(A)}$$

  Bayes' Rule, for any two events A and B , where P(B)  0, we have

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)} \tag{1.2}$$

This theory that we will use to develop our tools using Markov chains is a random model that describes a series of potential events where the probability of each event is determined only by the condition obtained in the previous event. Markov's separate series is an incalculably infinite series where the chain changes status in separate time increments

(DTMC). Consider the random process $\{\mathrm{X}_n, \mathrm{n} = 0, 1, 2, \ldots\}$ were $\mathrm{R}_{X_i} = \mathrm{S} \subset \{0, 1, 2, \ldots\}$ we sat that this process is a Markov chain if :

$$P(X_{m+1} = j \mid X_m = i, X_{m-1} = i_{m-1}, \ldots, X_0 = i_0) = P(X_{m+1} = j \mid X_m = i)$$

for all $m, j, i, i_0, i_1, \ldots, i_{m-1}$ If the number of states is finite, e.g.$\mathrm{S} = \{0, 1, 2, \ldots, \mathrm{r}\}$ we call it a finite Markov chain.

### Collaborative Filtering

Collaborative recommendation systems differ from content-based recommendation systems in that they use user assessments rather than component content. The collaborative liquidation algorithm aims to predict the usefulness of an element for an effective user $(u_a \in U)$ Based on similar user opinions or the user's own opinions on elements similar to the target element and thus generate better (N) Recommendations as those elements with the highest guess ratings.

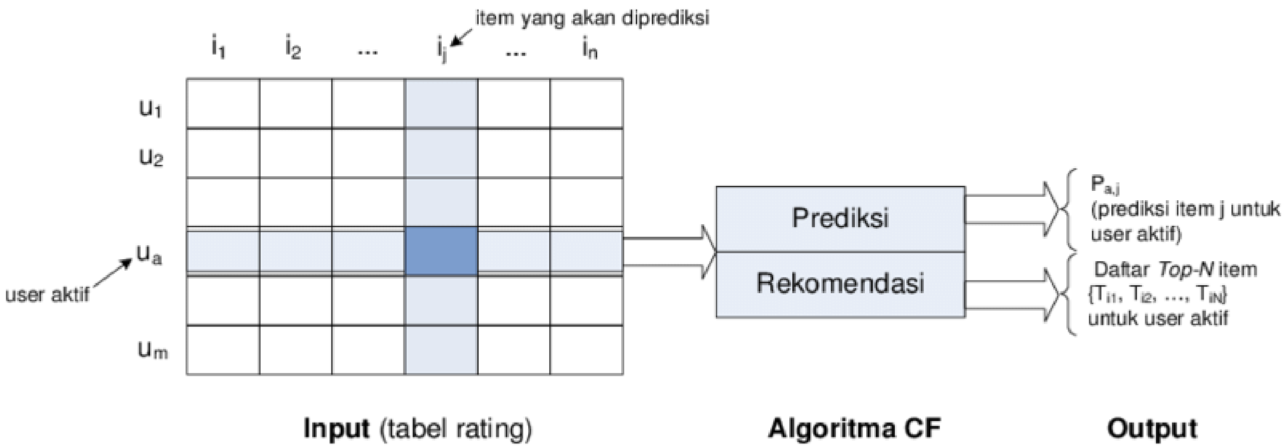



Figure 1.3: Collaborative Filtering Method [3]

Figure 1.3 shows the general method of a collaborative filter algorithm so that the value of the user's preference is expressed $(u_x)$ for an element$(I_i)$ For the evaluation component $(r_{u_x, I_i})$, while user assessment data are represented for the recommendation area elements in the matrix $(R[m \times n])$ in which each line represents a user while each column represents a specific element and represents the number at the intersection of each line and the user's valuation value column while the absence of that value determines that the user has not evaluated that element.

Overall, there are two main categories of collaborative filtering algorithms [22]:

- **Memory based technique** Collaborative memory-based filtering algorithms [23] use a specific type of machine learning method that is a neighbor's nearest algorithm (Neighborhood Near) that does not need to be pre-developed to build a preliminary predictive model in which predictions are made by aggregating assessments of the closest neighbors. To achieve the above, this method needs to store ratings, elements, and users in memory.

  Memory-based collaborative algorithms can be classified into two types:

  - **User–based** This method is one of the first automated cooperative liquidation techniques introduced first in the article recommendation system (GroupLens) [23],In this way the system searches for other users who have a similar valuation date (similar interests) to the effective user and recommendations are then made about the elements preferred by those similar users.
  - **Item–based** To solve the problem of scalability when the user database grows, collaborative element-based valuable algorithms [24] in which the similarities between element ratings models are calculated instead of calculating similarities between user ratings models, assuming that the user possesses similar preferences for similar elements, and thus this method is similar to the first content-based valid methods (Based-Content) But here the similarities of the elements are calculated using user ratings rather than extracting them from the item's data.

- **Modele based technique** Initially, most research in collaborative health systems focused on memory-based methods, but in recent years more attention has been paid to model-based techniques (based-model). Unlike memory-based models, model-based algorithms use a set of assessments.

  Users of the recommendation area elements with the aim of learning the Model Predictive (predictive model) are later used to generate recommendations for users.

  In general, the algorithms in this type of collaborative are based on the probable method of perceived collaborative filtering as calculating the expected value of the user's assessment against a particular element of the recommendation while giving its prior assessments to other elements.Thus the unknown valuation is calculated $(p_{u_a,I_i})$ By calculating the likelihood that an effective user $(u_a)$ It will give a specific assessment of the item ($I_i$) We have the Group ($I_{u_a}$) which represents the set of elements previously evaluated by the active user as shown in the following formula:

$$p_{u_u,I_i} = \sum_{i=0}^{n} i \times \Pr\left(r_{u_a,I_i} = \mathrm{i} \mid r_{u_a,I_j}, I_j \in I_{u_a}\right) \tag{1.3}$$

Assuming that the values of the ratings are in the field [0 - n]. Practically, the model construction process is carried out using different machine learning algorithms such as:

- **Bayesian network** The Bayesian network model [22] formulates a probability model for the collaborative filtering problem so that evaluations are used as training data for a bayesian network in which the contract elements correspond to the area of recommendation, while the node concurs with the potential values of each element. In this resulting network, each element will possess a set of better (predictors) for its assessments.
- **Clustering** The cluster model treats the problem of cooperative liquidation as a classification problem [25] and contracts similar users in the same group and thus assesses the possibility that a specific user belongs to a particular group of users with a view to using the evaluations of this group in order to calculate the probability of conditionality of this user's evaluations.
- **Rule-based** The rule-based method applies rule-finding algorithms between elements of the recommendation area and thereby generates recommendations based on the strength of the correlation between elements [26].

### Hybride Fitering

The term hybrid systems [27] is used to explain any advising system that integrates several recommendation techniques with the aim of taking advantage of their positives and overcoming their negatives and thus the possibility of generating recommendations of high accuracy and quality and thus establishing greater trust in the advising system by its users.

### 1.2.4 Phases of recommendation process

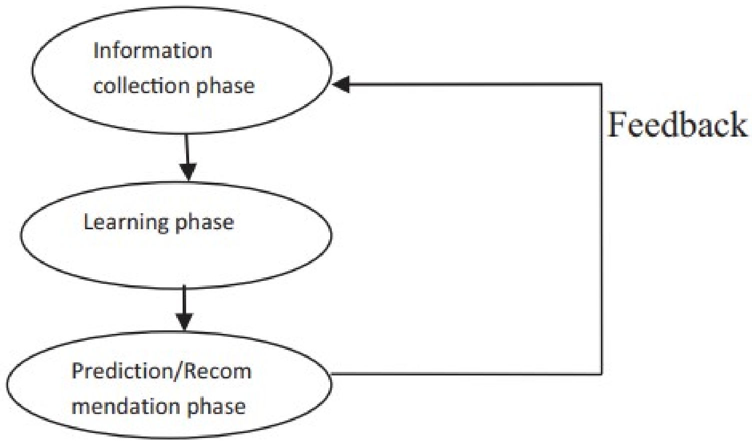



Figure 1.4: Recommendation Phases [1]

#### Information collection phase

This gathers pertinent user information to create a user profile or model for prediction tasks, such as the user's attributes, actions, and the content of the resources the user accesses. The user profile/model must be carefully created before a recommendation agent may work accurately. To deliver good recommendations straight away, the system needs to know as much as possible about the individual. Recommender systems use different inputs, such as the most convenient high-quality explicit feedback, w the user would like. This can be done directly using the dataset obtained during the information collection phase, which might be memory or model-based, or indirectly using the system's observed user actions. The steps of suggestion are highlighted in Figure 1.4. Comprises clear information from users about their interest in an item, or implicit feedback inferred indirectly from user behavior [28]. When explicit and implicit input are mixed, hybrid feedback is feasible.

#### Learning phase

It uses a learning algorithm to select and exploit the user's characteristics based on the feedback information collection phase.

#### Prediction/recommendation phase

It suggests or forecasts what sort of products

## 1.3 Context in Recommender Systems

The importance of contextual information has been recognized by researchers in several fields, including information retrieval, ubiquitous computing, marketing and management, etc. However, research on recommender systems has made little use of contextual information. Information such as time, location, and the company of other people can improve the recommendation process in some domains. Traditional recommender systems only deal with two types of entities, users and items. However, for many applications, such as recommender systems dedicated to tourism, it may not be sufficient to consider only users and items. It is often important to integrate information about the context. For example, a recommendation system for vacation stays must take into account the season to provide an adapted recommendation. Similarly, a recommendation system for tourism implemented on a mobile device can privilege the recommendation of places of activities close to the user's location.

### 1.3.1 Definition

Context is a vast notion for which it is particularly difficult to give a general and operational definition.[29] propose the following definition, which we quote and which is one of the most widely accepted:

Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves. However,

This definition has been criticized by Zimmermann [30] as being too general and not operational.

Zimmermann [30] define context as follows :"Context is any information that can be used to characterize the situation of an entity. Elements for the description of this context information fall into five categories : individuality, activity, location, time, and relations.

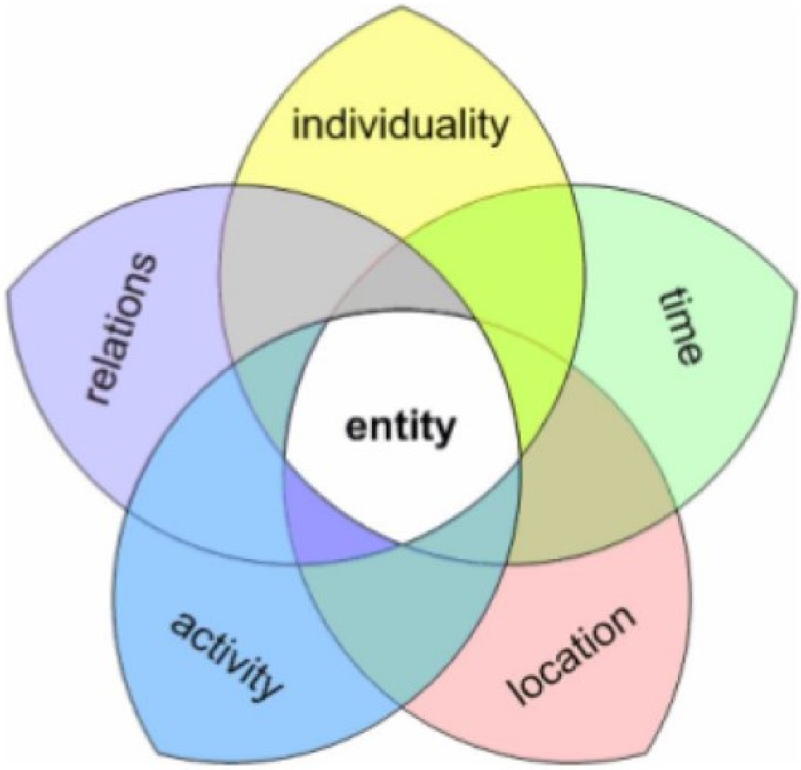



Figure 1.5: The different elements of the context [4]

### 1.3.2 Context modeling for recommender systems

Traditional recommendation systems are two-dimensional (2D) because they only consider the dimensions of the user and the item. In the context-integrated recommendation framework, the context is seen as additional information. In addition to the user and the item, we add the dimension of the context which will contribute to improve the recommendation provided by the system. A context sensitive recommendation system will therefore consider score functions in the form [31] :

$$\text{R : User} \times \text{Item} \times \text{Context} \rightarrow \text{Rating}$$

The rating function R is if we describe contextual information with a set of contextual dimensions D, two of which are User and Item, and the rest are contextual.

$$\text{R: D1} \times \ldots\ldots\ldots\ldots \times \text{Dn} \rightarrow \text{Rating.}$$

As we can see, contextual information can be of different aspects, such as time or location. Moreover, each contextual aspect may have a complex structure reflecting the nature of the contextual information (e.g., in the form of text). To cope with this complexity, contextual information is often hierarchical and represented as a tree.

### 1.3.3 Methods of incorporating the context

The incorporation of contextual information can be done at different stages of the process in a recommender system. Adomavicius and Tuzhilin [5]define three main approaches to contextualization depending on when the context is injected. These approaches are as follows:

- **Contextual pre-filtering**
- **Contextual post-filtering**
- **Contextual modeling**

We briefly present these three approaches in the following.

- **Contextual Pre-filtering** The incorporation of the context by pre-filtering or pre-processing consists in selecting a subset of data that is significant for the context in which one is situated and restricting the recommendation process to this subset. This implies building a model for each context. To illustrate this approach, let's take the example of a movie recommendation system that uses the temporal context: if a user wants to watch a movie during the weekend, only the movies available during the weekend are candidates for recommendation. available during the weekend are candidates for recommendation and only the ratings of users who only the ratings of users who have seen the movies during the weekend are used for the rating prediction. The use of this a priori filtering has been criticized, as the data set data set is reduced and can create problems for score prediction if the system does not have enough system does not have enough data.

- **Contextual Post-filtering** In a contextual post-filtering approach, the recommender system does not take into account In a contextual post-filtering approach, the recommender system does not take into account the contextual data during the recommendation process. The outputs of the recommendation algorithms are modified a posteriori to reorder the list of recommended items according to context. For example, a recommendation system for tourist places will use the geographical location of the user (location context), and may decide to eliminate a posteriori the recommendations of places that are too far from the user's location.

- **Contextual modeling** The context modeling approach consists of directly integrating contextual information into the recommendation process for item score prediction. To incorporate context, [Karatzoglou et al., 2010] propose tensor factorization methods. For these methods, in addition to the first two dimensions traditionally used for items and users, each type of context is considered as a new dimension. The score is no longer considered as a function with the two parameters item and user, but a function with the parameters item, user and context aspects.

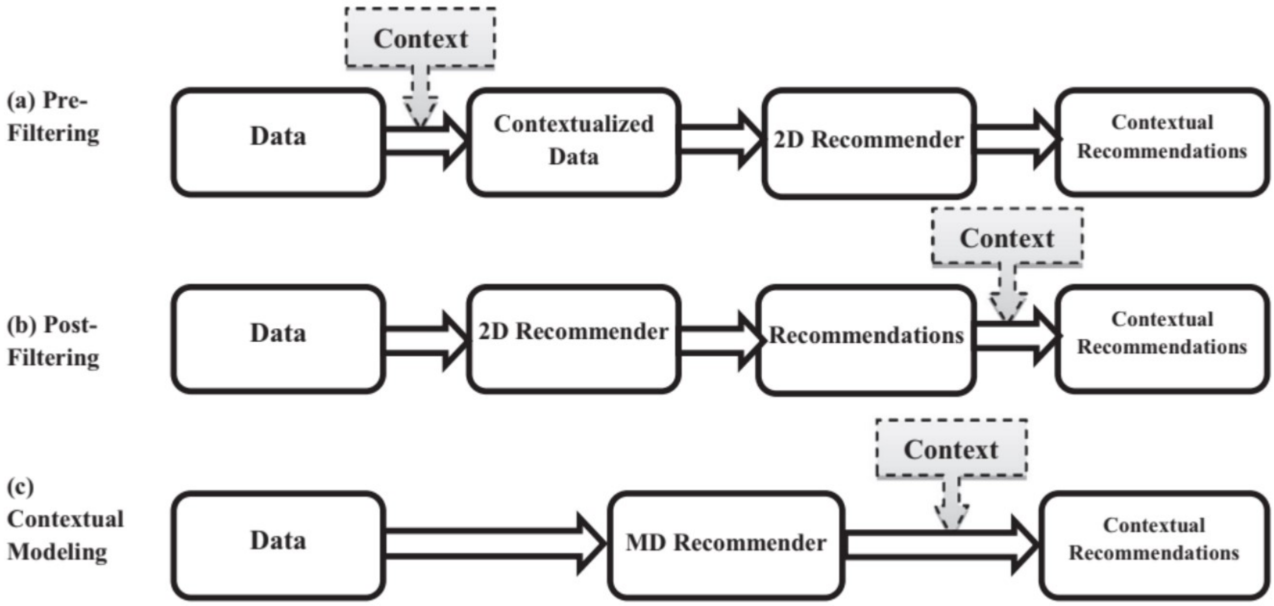



Figure 1.6: The incorporation of context in the recommendation process [5]

### 1.3.4 Context awareness

In general, context awareness refers to an application's capacity to detect and use contextual data, such as the user's position and adjacent gadgets. Shilit [32] was the first to propose the notion of context-awareness, which he characterized as an application's capacity to detect and respond to changes in the user's surroundings. Brown [33] describes it as "applications that may vary their behavior based on the user's situation." Dey [29] defines a context-aware application as one that leverages contextual information to give relevant information and services to the user, with relevance determined by the user's work. Several factors must be considered in order to effectively utilize the context and to establish a trustworthy method for developing context-aware services,several challenges arose [34]:

- **Context capture:** obtaining characteristics that define the user's context.
- **Context representation:** proposing a representation with high-level abstractions.
- **Context interpretation and reasoning:** reasoning about Context consists in deriving Context from the existing one at a high semantic level Service adaptation: services must be triggered and modified through produced scenarios.
- **Context management:** managing context consist of dealing with non-functional aspects.
- **Context reuse:** Using contextual characteristics to demand that their validity has expired.

## 1.4 Ontology

An ontology is a pre-existing word in philosophy science that refers to the science of natural existence [35] and in the field of artificial intelligence there are several different definitions of antagonism, the most famous of which is the definition of studer [36], which defines anthology as **"an explicit and formal characterization of a shared conceptualization perception of a particular field".**

Here we clarify some of the terms of the previous definition:

- **Conceptualization :** A simple model should be defined for the field studied at the conceptual level which defines the set of concepts, relationships and hypotheses found in the field.
- **Explicit :** The concepts used and their limitations must be defined clearly and directly.
- **Formal :** The representation method should be properly readable and interpretable by the machine.
- **Shared :** The characterization depends on the collective agreement of knowledge engineers to some extent.

### 1.4.1 Definition

In this thesis, we define ontology as an official model describing the area of recommendation considered as a set of preliminary concepts relevant to the area studied among the basic components of the recommendation system [36].

### 1.4.2 Components of Ontology

Officially, the ontology consists of a set of basic elements, the most important of which are:

- **Concepts or classes :** Concepts form the essence ontology, and the concept expression in ontology rewards grade expression in oriented programming. For example, in ontology what concerns the field of tourism the concept may be a city or place of hosting accommodation, and in general each concept has a specific number of features

- **Instances :** The class represents a range of actual purposes found in the field of study, for example the purposes Berlin and plaza hotel are two examples of the class city and accommodation respectively.
- **Property :** It is a bilateral connotation between rows, and from the most important relationships we have classification relationships that allow us to define a hierarchical structure between concepts (e.g. class football) is a class son of class sport and in addition to the classification relationships we have the purpose relationships that possess a specific field and scope. For example, the purpose relationships that possess a specific field and scope, for example, the pathological pathology locatedln knowledge between the concepts of accommodation and city helps us to represent the following truth: "the plaza hotel" is
- **Rules :** We can formulate hypotheses and rules using logic within the prescribed field. These rules are a translation of mathematical intuitions that allows for certain limitations to be imposed on a specific relationship or on the values that the attributes of a concept can take. so that these rules are utilized in order to apply complex evidentiary processes to obtain inferior, undescribed knowledge, For example, a hypothesis can determine that a semantic relationship (p) Between two rows is a transgressive relationship and so when the system knows that (a p b) and (b p c) can conclude that (a p c)

### 1.4.3 Ontology Classifications

Several classifications of ontology have been proposed, the most important of which are:

#### Classification of ontology by semantic spectrum

McGuinness proposed a classification based on the internal structure of the ontology content[37], and the gradient in this classification is from lightweight to heavy based on the complexity and evolution of the elements they contain as shown in the Figure 1.7:

- **Catalog :** A specific list of vocabulary that belongs to a specific area or application and is widely used in product classification systems in the field of electronic commerce.

- **Glossary :** A list of vocabulary that is explained by the use of natural language and therefore suffers from the problem of language ambiguity, for example our netGlos is a glossary of Internet terms in several languages.

- **Thesauri :** It explains and defines lexical concepts and connects them with each other within an organized structure containing relationships such as (tandem relationships, hierarchies, connection..) We have a collection of vocabulary encyclopedia, e.g. s Web encyclopedia (IEEE), which includes vocabulary associated with specific disciplines (engineering, technology, scientific, social...).

- **Informal is-a hierarchy :** It explains a hierarchical structure between concepts but the relationships between rows are not necessarily the relationship (is-a) in its exact sense and the most famous example of this species is our Yahoo Index of Titles.

- **Frames :** Models that explain rows and their characteristics and are used extensively in knowledge base modeling systems

- **ontology with value restrictions :** Limited functions are applied from the intended use of anthropology so that it can explain an area of values for the characteristics of the antagonistic concepts.

- **ontology with logical restrictions :** It is an onhology who explains the concepts, relationships and features as well as the logical rules governing the field of study.

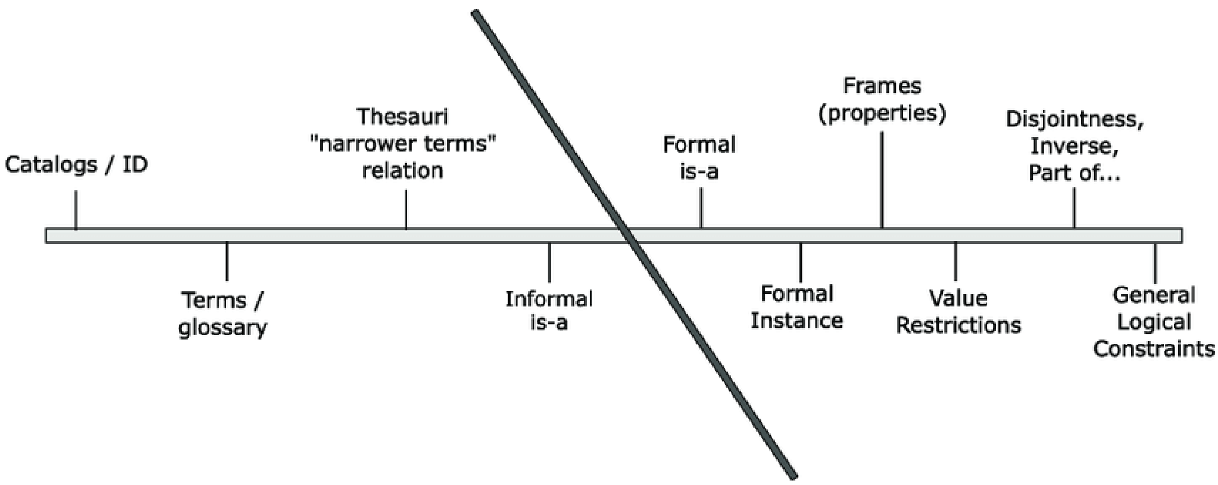



Figure 1.7: Classification Ontology by McGuinness [6]

### Classification of Ontology by generality

Guarino proposed a classification of antagonism according to its degree of reliance on a specific task or point of view as [38] shown in the Figure 1.8 :

- **Top-level ontology :** Used to represent a very general knowledge such as time or place and independent of any field or problem and can therefore be reused for the construction of other more customized ontology.
- **Domain ontology :** It focuses on the definition of concepts, relationships and basic rules of reasoning that belong to a specific field such as the field of automobiles and medicine.
- **Task ontology :** It explains the concepts that are used to carry out a particular task such as medical diagnosis or sales, by customizing the concepts found in high-level ontology.
- **Application ontology :** If we link a specific task to a specific field, we get an application ontology.

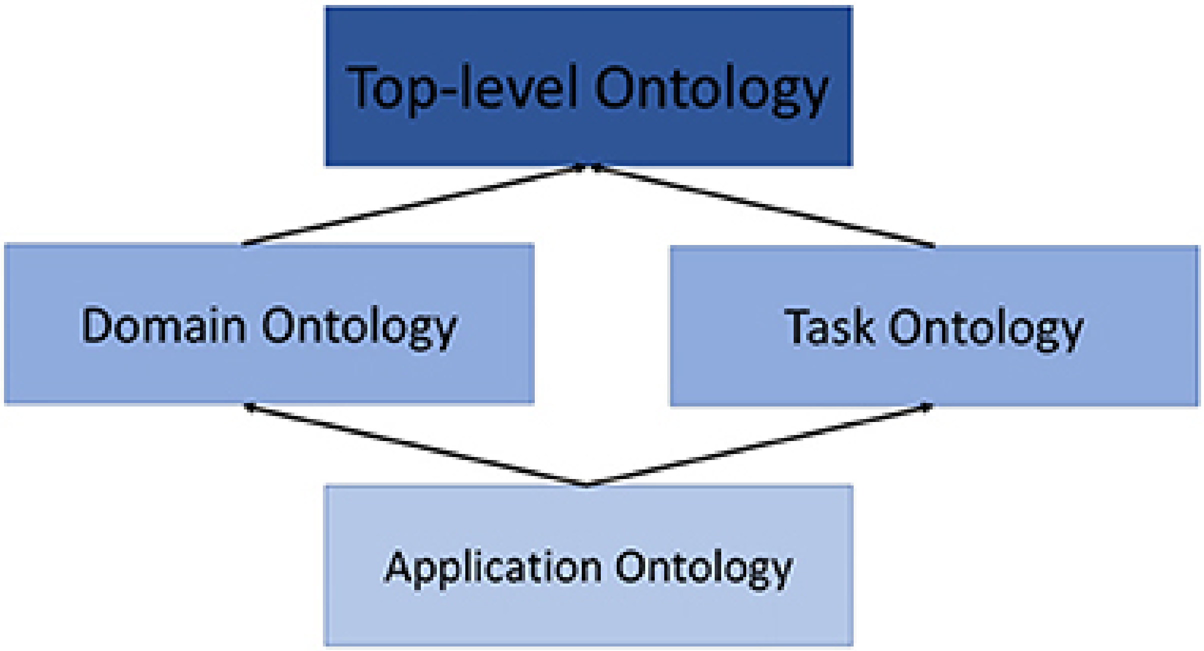



Figure 1.8: Classification Ontology by Guarino [7]

### 1.4.4 Ontology Development Process

METHONTOLOGY [39] is one of the most important approaches used to develop and evaluate the prototype of a studied field ontology so that this method is seen as a guide (set of guidelines) for the development and implementation of an ontology based on an adjustable replication model as illustrated in the Figure 1.9.

Below we are briefly explaining the basic phases of METHONTOLOGY:

- **Specification :** In this phase, the goal and field of ontology are determined, and at this stage, we need to obtain informal knowledge about the field of study.

- **Conceptualization :** This phase regulates and structures the knowledge collected in the first phase using external representations (graphic or tabular) independent of specific languages of achievement or development environments. This conceptual perception represents a semi-formal model of the field of study consisting of concepts and relationships between concepts.

- **Formalization :** At this phase, the conceptual model of ontology is transformed into an official model. The developer forms the classification and non-classification relationships between the basic concepts based on application requirements and defines the features of these concepts. For this phase, special tools can be used for the development of anthropology, which in turn automatically investigates the model of concepts in several anthropological languages such as protégé [40].

- **Implementation :** In this phase, the official antagonism model is achieved using a knowledge representation language such as OWL, which we will later explain.

- **Maintenance :** This phase modifies and corrects previously realized ontology and may lead to a new development cycle if unrealized or new requirements are identified.

- **Knweledge acquisition :** This phase uses several techniques to gather knowledge, such as interviews, questionnaires, text analysis, and other inference techniques.

- **Evaluation :** This phase uses several technical standards to verify the quality of the designed ontology.

- **Documentation :** This phase documents the details of the process of building an ontology.

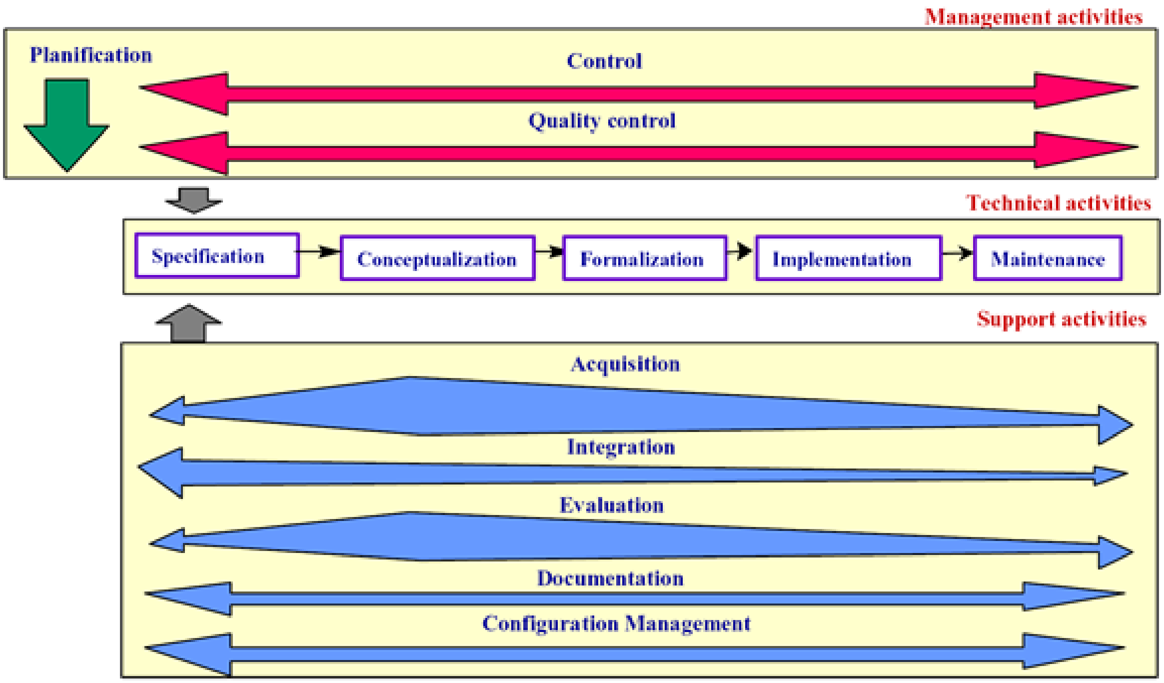



Figure 1.9: The process of the development of ontology by METHONTOLOGY method [8].

### 1.4.5 Ontology Web Language

One of the most popular modeling languages in the semantic web has been introduced by W3C to represent complex and rich knowledge about the sources and relationships between them and the intuitions and rules governing the field of study.

OWL language relies on formal logic in the representation of knowledge, allowing us to implement logical reasoning within the knowledge base to verify the coherence of that knowledge or acquire implicit knowledge, so that there are three sublanguages of OWL that differ from each other in the degree of expression and complexity (so that the more expressive capacity the accompanying complexity increases) [41]:

- **OWL-Full**
- **OWL-DL**
- **OWL-Lite**

## 1.5 Conclusion

This chapter has elaborated on the recommendation's accession and relevance in recent years. Next, we discussed the importance of context in the field of recommender systems by presenting the different sources of contextual information as well as the different paradigms of context incorporation for recommender techniques. Finally, we learned about the ontology , and we reviewed in detail the techniques, types and structure of ontology. Until now, we've successfully layed down all the preliminary knowledge that the reader needs to progress further in this report.

The next chapter is devoted to the work applied to these concepts.

# CHAPTER 2

# RELATED WORKS

## 2.1 Introduction

In this chapter we address the work and applications of researchers in context-awareness recommendation systems as well as the importance of ontology in structuring the concepts of the recommendation's accession in different areas.

## 2.2 Recommendation systems using contextual information

- **on September 2011** [5] The value of contextual information has been acknowledged by (Gediminas Adomavicius, Alexander Tuzhilin) in many disciplines they argued that relevant contextual information does matter in recommender systems and that it is important to take this contextual information into account when providing recommendations. they also explained that the contextual information can be utilized at various stages of the recommendation process, including at the pre-filtering and the post-filtering stages and also as an integral part of the contextual modeling, Table 2.1 shows some work on adding contextual information. researchers and practitioners have also showed that various techniques of using the contextual information, including these three methods, can be combined into a single recommendation approach, and they presented a case study describing one possible way of such combining.

Table 2.1: The mechanisms of four consensus filtering approaches

| References | Pre-filtering | Post-filtering | Contextual Modeling |
|---|---|---|---|
| Liu et al.[42] | | | √ |
| Kolahkaj et al.[43] | | | √ |
| Adomavicius et al.[31] | √ | | |
| Zheng et al.[44] | | | √ |
| Ferdousi et al.[45] | √ | | |
| Gupta et al.[46] | | | √ |
| Zheng et al.[47] | | √ | |
| Chen [48] | | | √ |
| Linda et al. [49] | | | √ |
| Codina et al. [50] | √ | | |
| Ramirez et al.[51] | | √ | |

- **on 28 septembre 2014** [11] a research paper was published titled A systematic review of context-aware recommender systems written by Zohreh Dehghani. The paper is about the relvant articles in the field of scholar recommendation that the contextual information are categorized in three context, namely users' context, document's context, and environment context. The most recommending approaches are collaborative filtering content based , knowledge based and hybrid this review has been conducted to identify the contextual information and methods used for maleing recommendations digital libraries as well as the way researchers understood and used relvant contextual information systematic review methodology.

- **on 28 september 2015** [52] a research paper was published titled context-based collaborative filtering for citation Recommendation written by X.kong et al, The paper is about citation recommendation as an important area of a research and its role in suggesting relevant references .The author provides a novel citation recommendation method in which just the easily detained citation relation are used as a source data . Bigger value of yields association possibility based on the cumulative distribution function as stated in Equation (2.1):

$$\text{sim}_{i1,i2} = \frac{V_{i1} \cdot V_{i2}}{|V_{i1}| \cdot |V_{i2}|} \tag{2.1}$$

  where Vi1 and Vi2 are the paper vectors of citing papers i1 and i2.

  The research examines the experimental findings of CCF different values of ts on two datasets (HEP-PH and HEP-TH ) in order to batter understand the impact of ts on suggestion quality .He offers a citation recommendation approach (CCF) for recommendation appropriate publication as references for a target work in this study, the reasoning behind this similarity estimate is that citing articles are considered comparable if the co-occurred with other citing papers.

  Their suggested CCF significantly outperforms Baseline in the three evaluation metrics, as demonstrated by these experimental findings on the two datasets. This also suggests that using citation context to calculate similarity might help create more accurate suggestions.

- **In 2018** [53] was posted a research paper titled artificial intelligence Scientific documentation dataset for recommender system, written by Fernando Ortega. The paper provided collaborative filtering datasets called SD4AI (Scientific Documentation for Artificial Intelligence), because Not only can public datasets make the design, development, and testing of new general Artificial Intelligence (AI) approaches and algorithms more easier. The Scientific Documentation Dataset give help to further AI research in the field of Scientific Documentation (SD), particularly study in RS Machine Learning (ML) approaches. The fundamental goal of their work is to give the required resources and experimentation foundation so that the (SD) field might benefit from the present RS field's advancements and beyond. They use of SD4AI dataset, for can make recommendations of topics from a paper, recommendations of papers from a topic, related papers, related topics, etc. The existing scientific documentation-based recommender systems focus on exploiting the citations and references information included in each research paper and also the lists of co-authors.

- **On 13 march 2020** [54] was published a research paper titled by collaborative approach toward scientific paper Recommendation using citation written by Nazmus Skib. the number of scientific publication is rapidly increasing on the web is a difficult problem in finding relevant papers to research interest. their paper presents a collaborative filtering based recommendation approach for scientific papers that does not depend on priori user profiles and which utilizes only public contextual information . by Use citation context,they utilized 2-level paper-citation relations to find hidden associations between papers. The rational underlying this approach is that, two papers are co-occurred with same cited paper(s) and two papers are co-occurring with same citing paper(s) are significantly similar to some extent . and so improve recommendation systems.

## 2.3 Recommendations systems based on ontology

**in 2021** [12] was posted a brief review of ontology-based recommendation for context aware presented by (Umair Javed, Kamran Shaukat).Their work discloses that the ontology-based recommendation system, combined with other recommendation techniques, is universally used to recommend context-aware resources. Ontology domain knowledge can efficiently contribute to enhance the accuracy and quality of recommendations. However, cold-start drawbacks remain the same. For future work, there are three context-aware recommendation system) architectural models that are contextual pre-filtering, contextual post-filtering, and contextual modelling. they will try to overcome challenges that they face in pre-filtering models that are context over-Specification that include the Sparsity problem: overly specified context may not have enough training examples for accurate prediction Generalization in which they use latent factors models or dimensionality reduction approaches to overcome this problem. they can further apply context-aware splitting approaches based on contextual pre-filtering to produce a 2D data set that incorporates context information associated with preference results. This will also lead to the sparsity problem, which they will need to overcome. researchers can also introduce semantics into the similarity of contexts to further alleviate the sparsity of contexts. they can also introduce factorization in contextual modelling to fit the data using various models. One of them is tensor factorization that can extend the twodimensional matrix factorization into a multi-dimensional version of the same problem and then multi-dimensional into lower-dimensional representation. they can also implement various statistics and data mining techniques present to thier data to get accurate and more specific contextual information.

## 2.4 Conclusion

As previously suggested by researchers and writers, the quotation-based recommendation systems of the paper recommendation have an important and significant role to play in solving the problems and challenges faced by researchers in locating the most important scientific papers of their work or studies through the vast amount of information online. The addition of contextual information broadly improves the paper recommendation. Contextual information constitutes an effective approach to developing a more precise, relevant and quality recommendation, but there is no proposal by researchers for relevant scientific paper recommendation systems to add contextual information using the ontology that we will address in the next chapter.

# CHAPTER 3

# IMPLEMENTATION

## 3.1 Introduction

In this chapter we suggest the proposed intelligent algorithm MASSPR and ontology on which it is based to filter the most important papers, as we briefly explain the steps of implementation of both the ontology and algorithm and finally discuss the results obtained against the results of the ACM Dl library.

## 3.2 Ontology RS

Ontology is one of the most powerful tools to represent the field of knowledge. So we proposed an Ontology for scientific research so as to facilitate the process of recommending useful papers to researchers in their field of research. We elaborate on some details in our ontology Knowledge Model called Onto-RS (Ontology in Research Scientific) shown in Figure (3.5). The proposed ontology model includes several different elements such as basic concepts of scientific research and relationships between these concepts, such as articles, author, journal, venues, etc., and explains mechanically interpretable definitions, and we have incorporated contextual information into Onto-RS concepts to make more accurate recommendations. The formal context model based on anthropology can play a vital role in facilitating thinking by formally representing field knowledge.

### 3.2.1 Papers

Generally is the in-depth scientific study in which the researcher or group of researchers briefly makes scientific research content. They are published in a journals, which is dedicated to publishing this type of work. They are subjected to peer evaluation. That the work has been reviewed by numerous experts in the area who have verified the quality of the writing as well as the correctness of the authors' analysis and findings. There are citations in them. This indicates that the study regularly refers to earlier publications that are relevant to the topic at hand. At the conclusion of the article, a reference section lists all of the books that were cited. The general outline/flow is as follows:

- **Title**
- **Author(s)**
- **Abstract**
- **Introduction**
- **Results**
- **Discussion**
- **References**
- **They follow a standardized style of writing and data presentation.**

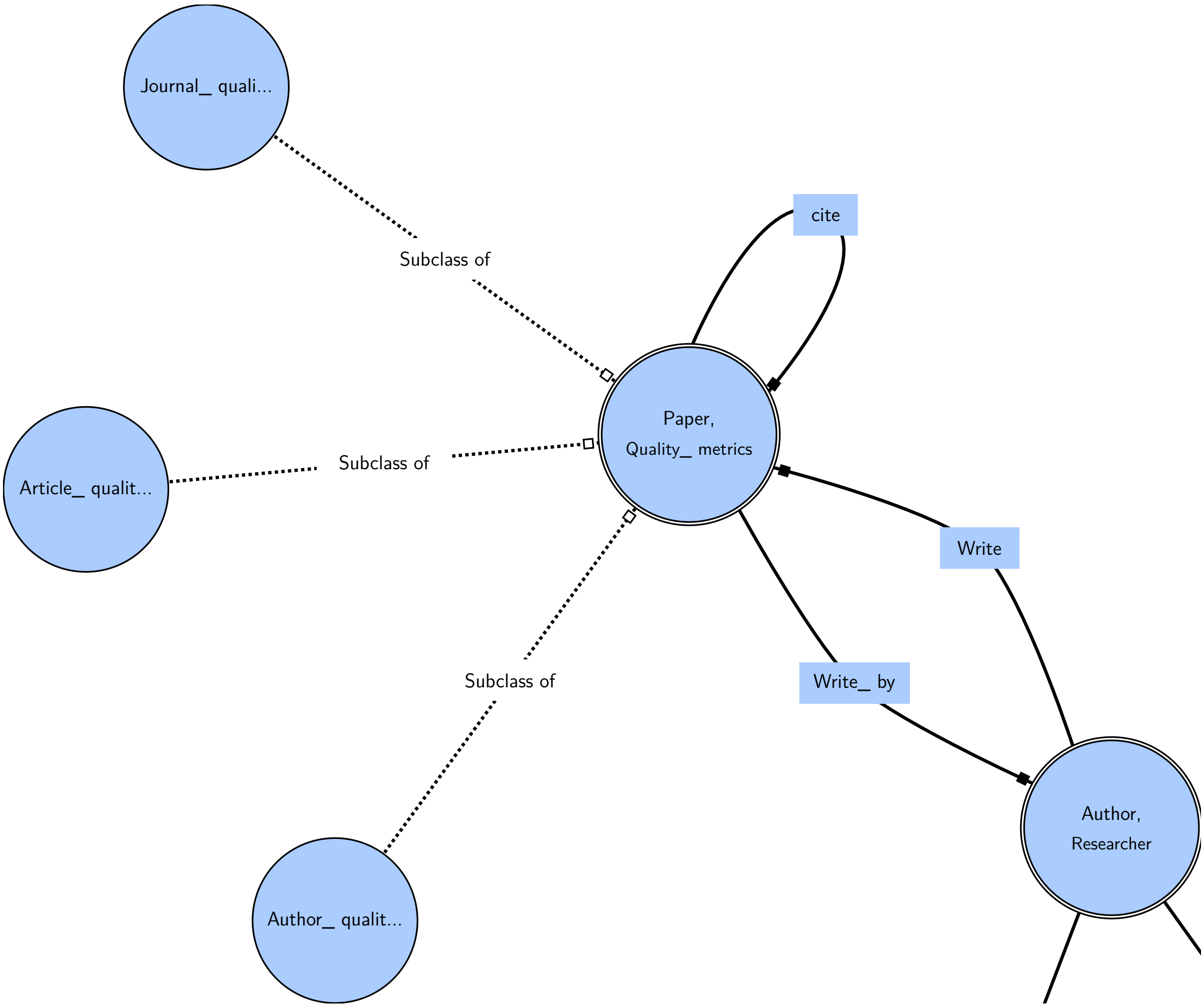



Figure 3.1: Paper Concept in Onto-RS

### 3.2.2 Author

The author is the person who writes the article or scientific paper that is published in journals and can be more than one person. If more than one author writes an article, one person will choose to be the corresponding author. This person will handle all correspondence about the article and sign the publishing agreement on behalf of all authors.

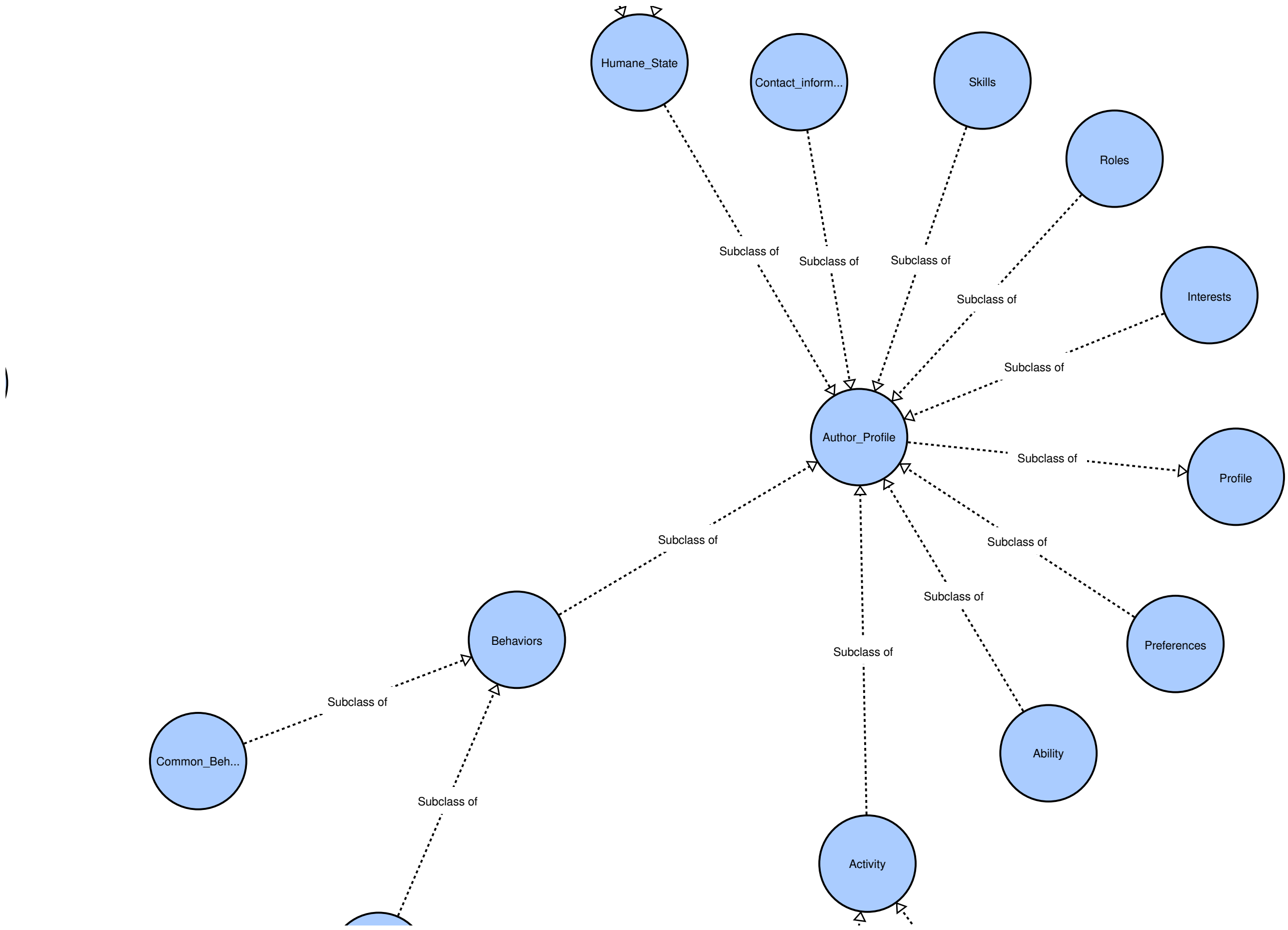



Figure 3.2: Author concept in Onto-RS

### 3.2.3 Journal

It is a factual or electronic rule with a lot of research, reports, works and information that journals issue and publish periodically. It means that it is published daily, weekly, monthly or annual and is determined by the journal own activity. And these journals cover a lot of attitudes and events, so a lot of people think that the journal and the paper are the same concept, but they differ in the magazine is a small book, and the newspaper is a big paper. But they are similar in that they are considered a newspaper.

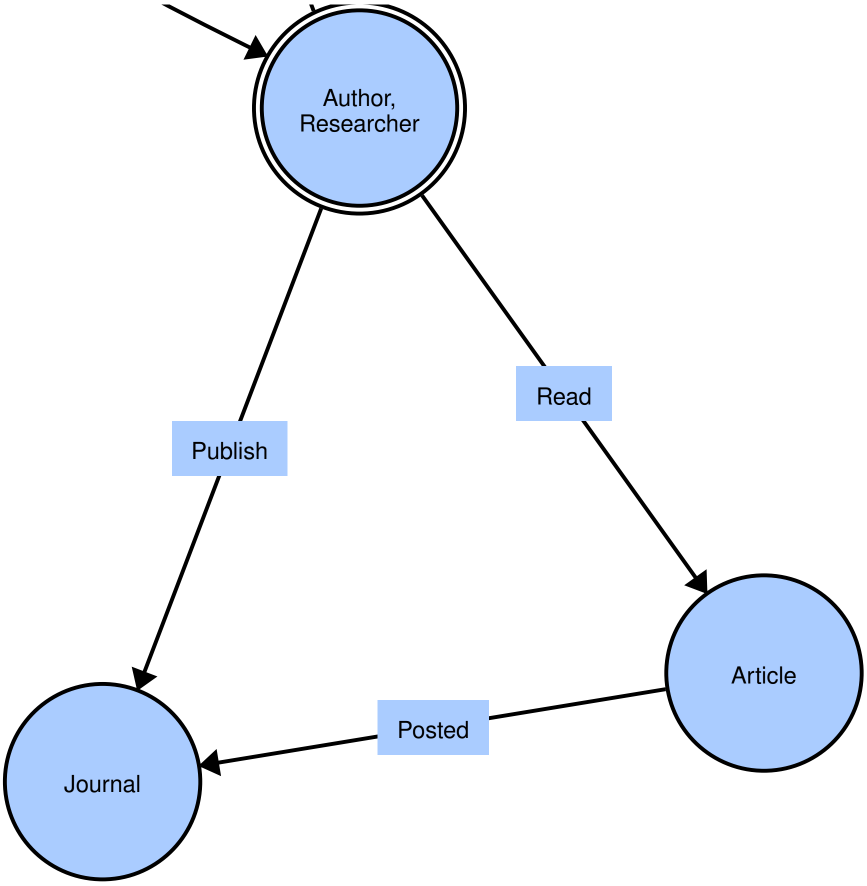



Figure 3.3: Journal concept in Onto-RS

### 3.2.4 Context

We elaborated on its definition in chapter 1, but in this part we adopt this definition to our method as: ' the context is a structured information model. That information related to each other logically in order to characterize a "Thing" from multi-dimensions. A 'Thing' is considered as "situation", 'person', 'event', 'place', 'Object', 'software' [55] .

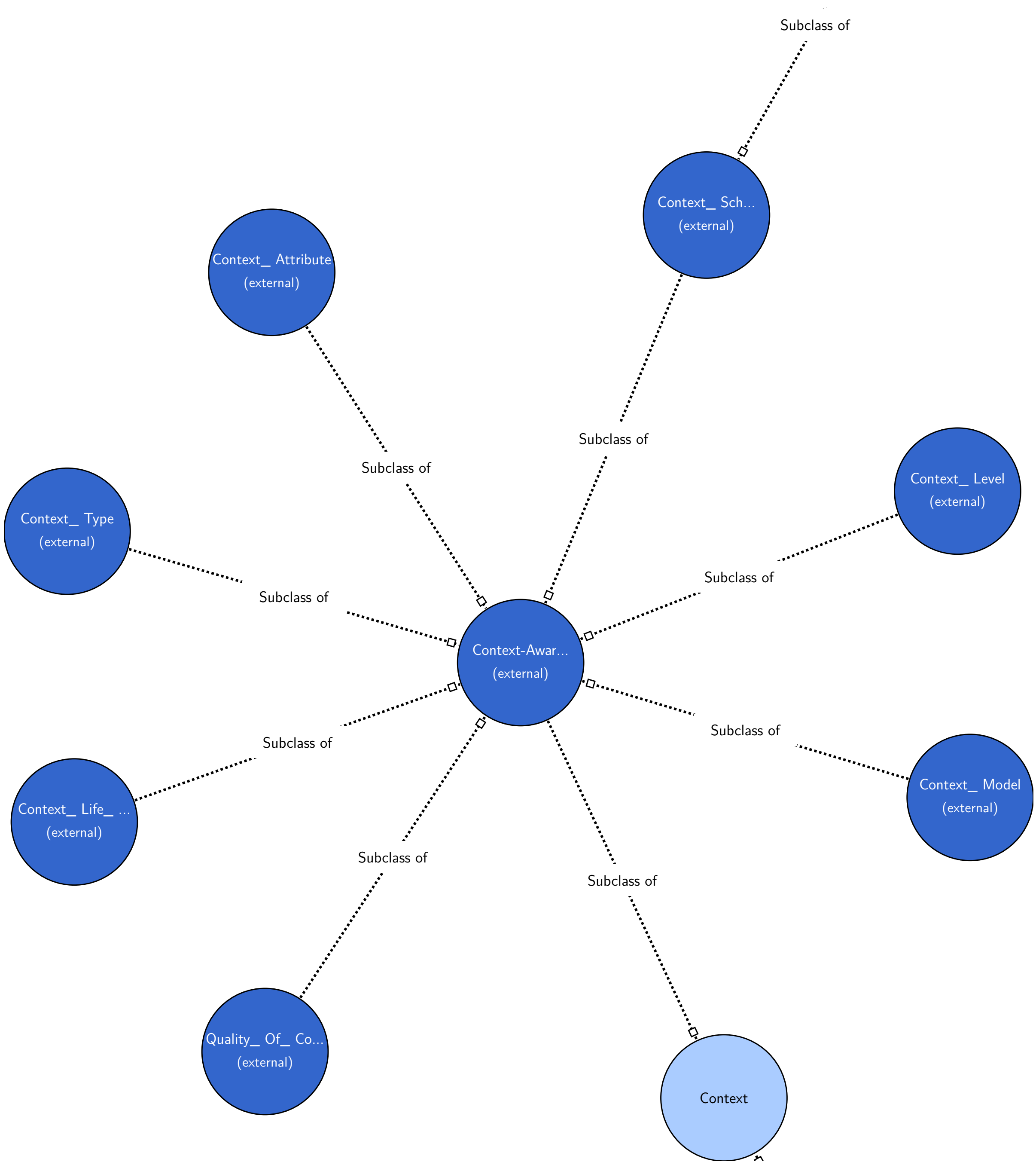



Figure 3.4: Context concept in Onto-RS

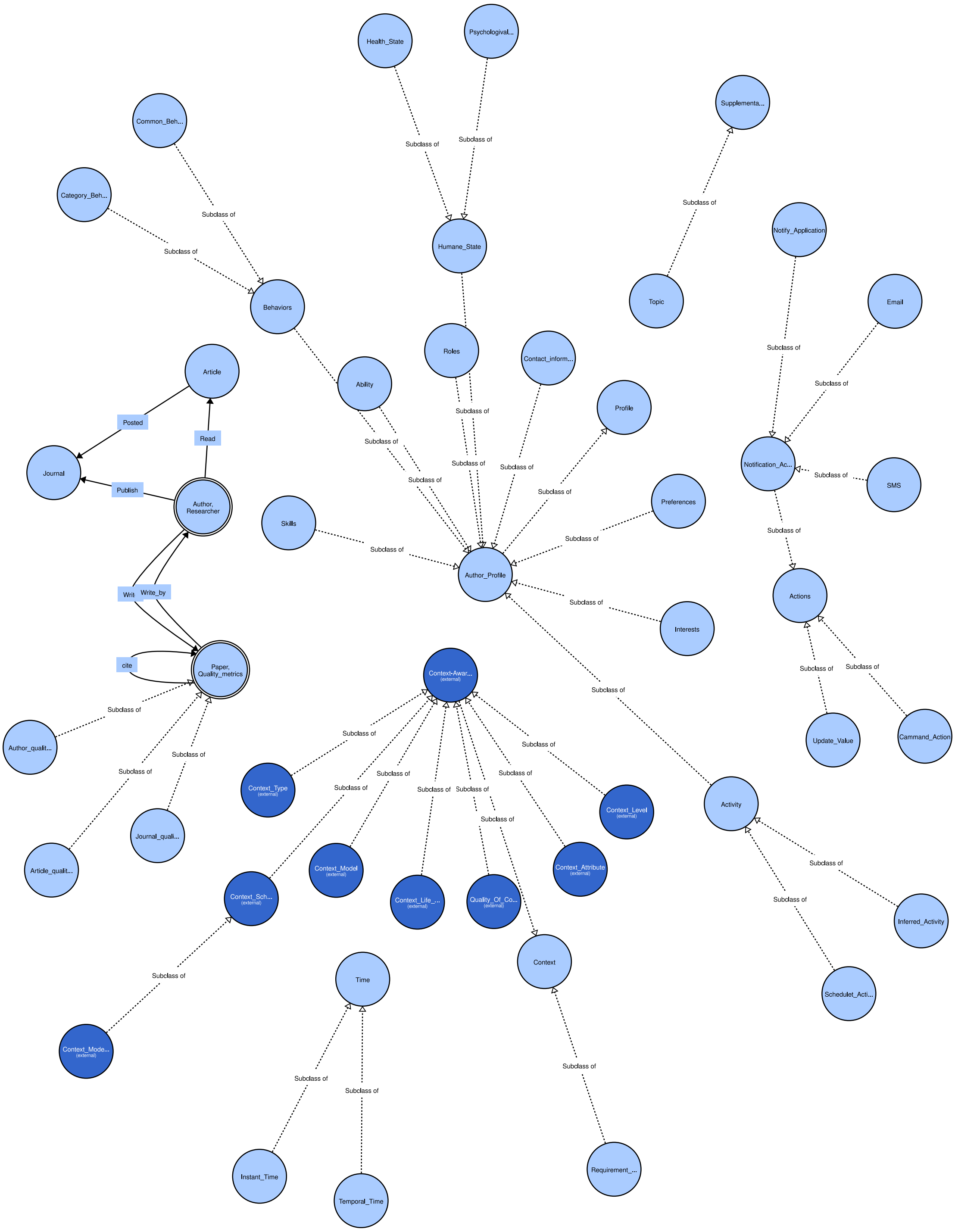



Figure 3.5: Proposed ontology (Onto-RS)

## 3.3 MASSPR Algorithm

The main idea behind the felting algorithm MASSPR Multi-Agent System for Scientific Paper Recommendation Based on Intelligent Mechanism that we develop based on Bayes and Markov a chain theorems which we explained earlier. The first step start by ontology Onto-RS building a graph of nodes contains from words and articles. The graph nodes are linked with each other by semantic relationships. Each word has three kinds of semantic relations. First, the PW witch represents The Probability of Exiting the Word in a Scientific Paper. Second, the Pwc witch measure The Probability of Exiting the Word incited a paper. And third, the Pwa represents The Probability of Exiting the Word in else author's Papers. These three probabilities will be used in the following formula to compute the word node power :

$$\text{Word\_Node\_Power} = \textstyle\sum_{i=0}^{m} P_{w_i} + \sum_{j=0}^{n} P_{wc_j} + \sum_{k=0}^{h} P_{wa_k}$$

The word node power will be used later to compute the article node power. The article node has more than three semantic relationships besides the three presented in the word power. The fourth is the CBP, which indicates that Paper 1 cites paper 2. Next to the PMA, which measures The Probability of mutual authors. Finally, the CSP represents The Probability of both papers cited in the same paper.

The Formulas to compute the Article node power are:

$$\text{Article\_Node\_Power}_{\ 0} = \textstyle\sum_{i=0}^{m} Cbp_i + \sum_{j=0}^{n} \text{Pma}_{\ j} + \sum_{k=0}^{h} C_{spp_k} + \sum_{z=0}^{f} \text{Word\_Node\_Power}_{\ 0_z}$$

The Formula to compute the Article node power :

$$\text{Article\_Node\_Power}_{\text{id}} = \left(\frac{\text{P(Article\_Node\_Power}_{\text{ id}} \cap \text{Article\_Node\_Power}_{\text{ id - 1}})}{\text{P(Article\_Node\_Power}_{\text{ id - 1}})}\right) * \left(\sum_{i=0}^{m} \text{Cbp}_{id_i} + \sum_{j=0}^{n} P_{ima_{id_j}} + \sum_{k=0}^{h} C_{sp_{id_k}} + \sum_{z=0}^{f} \text{Word\_Node\_Power}_{\ id_z}\right)$$

$$, i > 0.$$

**Algorithm 1:** Masspr algorithm

**Data:** Pw, Pwc, Pwa, Cbp, Pma, Csp
**input** : Articles_List, N_Words, Top_Nb_Articles
**Output** : Masspr_Graph
**Result:** Recommended_Articles_List

```
Words_List ← Extract_Words(Articles_List);
Masspr_Graph ← Initialization_Graph_Nodes(Words_List, Articles_List);
Initialize(Filtring_Agents , Recommended_Articles_Buffer);
begin
    Words_Probability_List ← Counting_Probability_Of_Existence(Words_List);
    Masspr_Graph ← Update_Graph(Words_Probability_List);
    for Word ∈ Masspr_Graph do
        Pw ← Assigning_Task_To_Agents(Word, Pw_Counting_Agents) ;
        Pwc ← Assigning_Task_To_Agents(Word, Pwa_Counting_Agents) ;
        Pwa ← Assigning_Task_To_Agents(Word, Pwc_Counting_Agents) ;
        Masspr_Graph ← Update_Graph(Pw, Pwc, Pwa, Word);
    for Article ∈ Masspr_Graph do
        Cbp ← Assigning_Task_To_Agents(Article, Cbp_Counting_Agents) ;
        Pma ← Assigning_Task_To_Agents(Article, Pma_Counting_Agents) ;
        Csp ← Assigning_Task_To_Agents(Article, Csp_Counting_Agents) ;
        Masspr_Graph ← Update_Graph(Cbp, Pma, Csp, Article);
    while (Size(Articles_List) > Top_Nb_Articles && Entropy_H < Learning_Rate_Entropy) do
        for (Node ∈ Masspr_Graph) do
            if (Node ∈ Words_List ) then
                Assigning_Task_To_Agents(Node, Pw_Counting_Agents) ;
                Assigning_Task_To_Agents(Node, Pwa_Counting_Agents) ;
                Assigning_Task_To_Agents(Node, Pwc_Counting_Agents) ;
```

$$Word\_Node\_Power \leftarrow \sum_{i=0}^{m} Pw_i + \sum_{j=0}^{n} Pwc_j + \sum_{k=0}^{h} Pwa_k$$

```
                if (Word_Node_Power < Learning_Rate) then
                    Remove_Node_Agents ← Assigning_Task_To_Agents(Node) ;
                    Update_Graph_Agents ← Assigning_Task_To_Agents(Masspr_Graph) ;
                else
                    Update_Graph_Agents ← Assigning_Task_To_Agents(Node, Word_Node_Power)
            else if (Node ∈ Articles_List) then
                Id ← GetArticleID(Node) ;
                Define_Predecessor_Agents ← Assigning_Task_To_Agents(Node, Masspr_Graph);
                Assigning_Task_To_Agents(Node, Cbp_Counting_Agents) ;
                Assigning_Task_To_Agents(Node, Pma_Counting_Agents) ;
                Assigning_Task_To_Agents(Node, Csp_Counting_Agents) ;
                if (Id = 0 | Iteration = 1) then
```

$$Article\_Node\_Power_{id} \leftarrow \sum_{i=0}^{m} Cbp_i + \sum_{j=0}^{n} Pma_j + \sum_{k=0}^{h} Csp_k + \sum_{z=0}^{f} Word\_Node\_Power_{id_z}$$

```
                else if (Id > 0 & Iteration > 1) then
```

$$Article\_Node\_Power_{id} \leftarrow \left(\frac{P(Article\_Node\_Power_{id} \cap Article\_Node\_Power_{id-1})}{P(Article\_Node\_Power_{id-1})}\right) * \left(\sum_{i=0}^{m} Cbp_{id_i} + \sum_{j=0}^{n} Pma_{id_j} + \sum_{k=0}^{h} Csp_{id_k} + \sum_{z=0}^{f} Word\_Node\_Power_{id_z}\right)$$

```
                if (Article_Node_Power_id < Learning_Rate) then
                    Remove_Node_Agents ← Assigning_Task_To_Agents(Node) ;
                    Update_Graph_Agents ← Assigning_Task_To_Agents(Masspr_Graph) ;
                else
                    Update_Graph_Agents ← Assigning_Task_To_Agents(Node, Article_Node_Power_id) ;
            Update_Graph_Agents ← Assigning_Task_To_Agents(Articles_List)
```

$$Entropy\_H \leftarrow \sum p(Node_{id}) \log_b p(\frac{1}{Node_{id}})$$

```
    Recommended_Articles_List ← Sorting_Descending_Order(Articles_List)
```

Figure 3.6: MASSPR algorithm

## 3.4 Implementing Onto_RS Ontology

We start by the implementation of our Research scientific ontology. To have a machine-readable ontology, we use the Protege5 ontology editor [48]. This editor allows translating the ontology in different languages like the OWL [49]. We create all our hierarchical classes, and we add for each concept its properties and relationships as shown in Fig. 7. The Ontology rules are an important . They define the way to exploit Research scientific ontology.Then we use WebVOWL a web application for the interactive visualization of ontology. It implements the Visual Notation for OWL Ontology (VOWL) by providing graphical depictions for elements of the Web Ontology Language (OWL) that are combined to a force-directed graph layout representing the ontology. Interaction techniques allow to explore the ontology and to customize the visualization. The VOWL visualizations are automatically generated from JSON files into which the ontology need to be converted. A Java-based OWL2VOWL converter is provided along with WebVOWL.

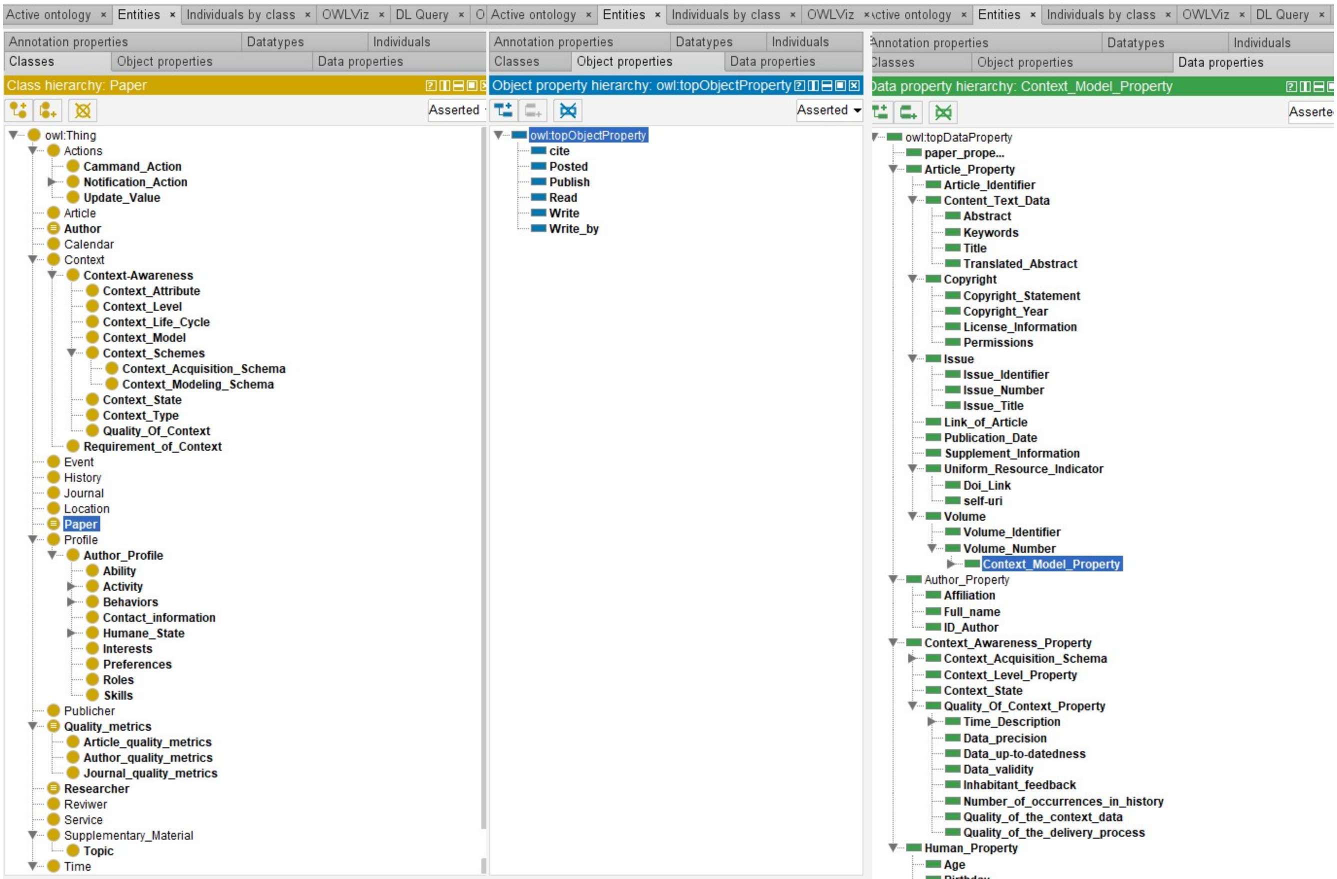



Figure 3.7: The implementation of our Ontology (Onto_RS) in Protege 5

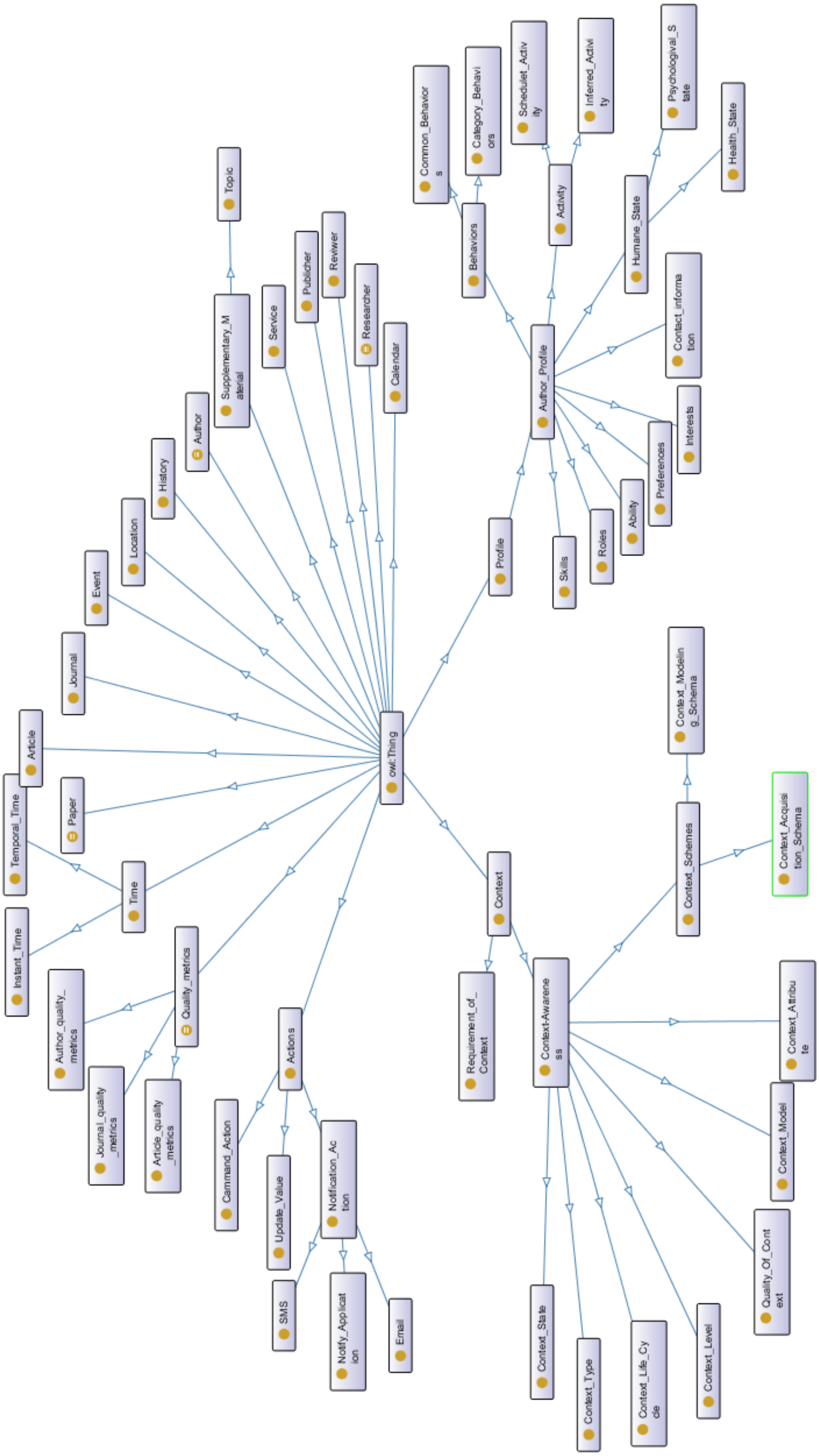



Figure 3.8: The OntoGraf of Onto_RS

## 3.5 Implementing MASSPR Algorithm

The next, we used To develop the MASSPR tool the JAVA programing language and Eclipse IDE as the environment of development. First, we start by developing the kernel of the MASSPR system that includes all the necessary modules and their functions. Then, we implement the Searching and filtering Agents using the JADE (Java Agent Development Framework). It is a software framework fully implemented in the Java language. It simplifies the implementation of multi-agent systems through a middle-ware that complies with the FIPA specifications. There are many JAVA codes and classes that were developed in the path to constructing the MASSPR kernel. Such as the ACM-Crawling-API, which provides tools to browse the ACM digital library to collet scientific articles data. This library is fully adopted with ACM DL and allows MASSPR users to collect the number of research papers they need. Second, we exploit the JavaFx to develop the MASSPR GUI (graphic user interface) to allow users to interact with our system and benefit from its functionalities. The JavaFX is a set of graphic packages that enable developers to design and deploy a rich client application that operates consistently across diverse platforms. Finally, we linked and merged everything to produce the complete first version of the MASSPR tool.

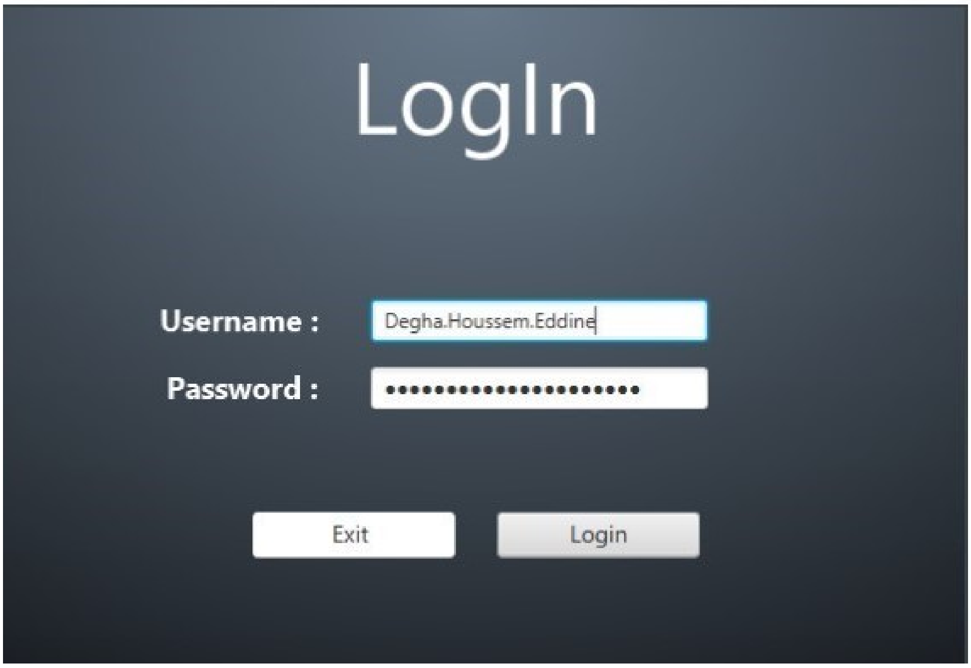
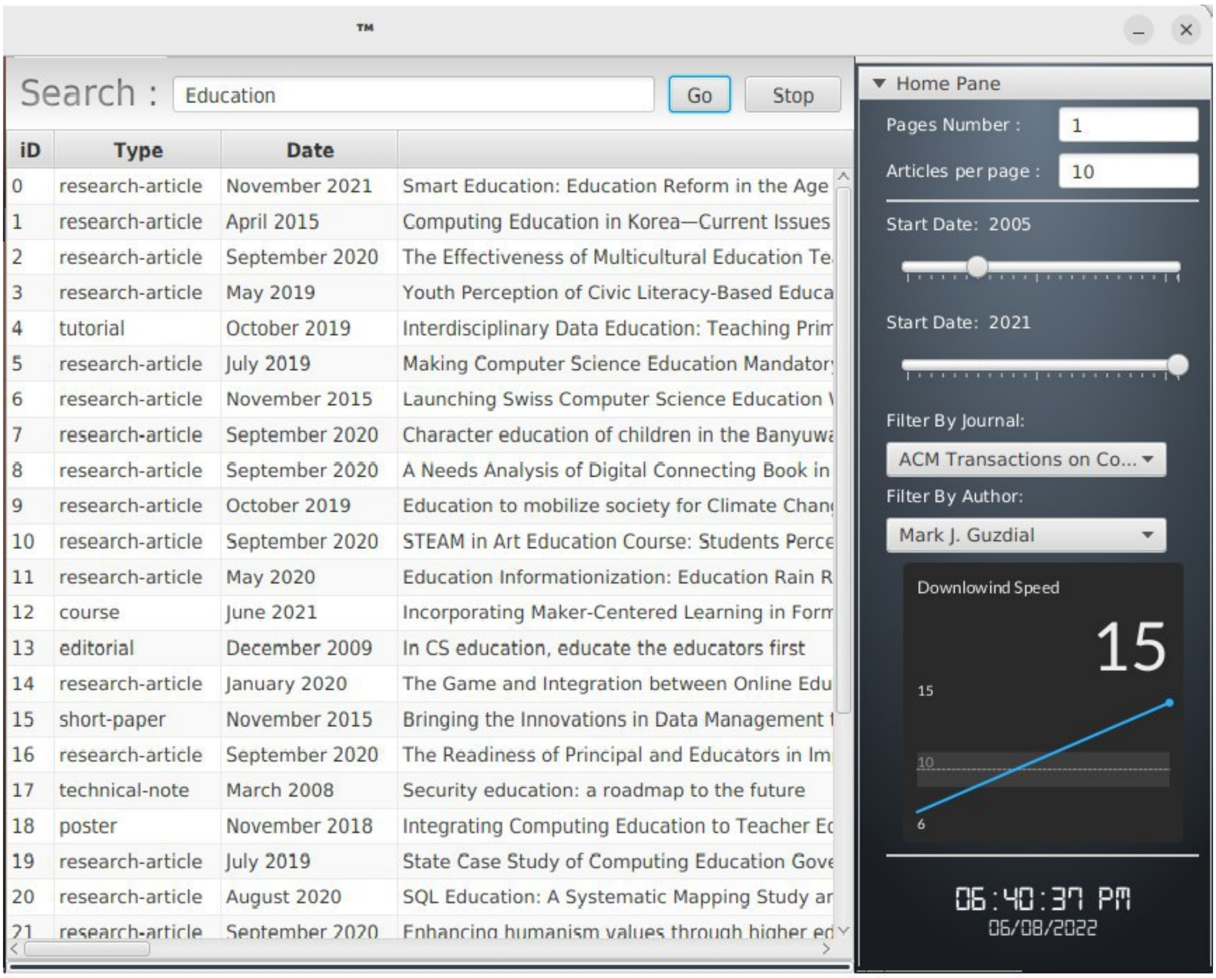



Figure 3.9: Screenshot of the Login windows of the MASSPR-Tool.




| iD | Type | Date | |
|---|---|---|---|
| 0 | research-article | November 2021 | Smart Education: Education Reform in the Age |
| 1 | research-article | April 2015 | Computing Education in Korea—Current Issues |
| 2 | research-article | September 2020 | The Effectiveness of Multicultural Education Te |
| 3 | research-article | May 2019 | Youth Perception of Civic Literacy-Based Educa |
| 4 | tutorial | October 2019 | Interdisciplinary Data Education: Teaching Prim |
| 5 | research-article | July 2019 | Making Computer Science Education Mandator |
| 6 | research-article | November 2015 | Launching Swiss Computer Science Education |
| 7 | research-article | September 2020 | Character education of children in the Banyuwa |
| 8 | research-article | September 2020 | A Needs Analysis of Digital Connecting Book in |
| 9 | research-article | October 2019 | Education to mobilize society for Climate Chan |
| 10 | research-article | September 2020 | STEAM in Art Education Course: Students Perce |
| 11 | research-article | May 2020 | Education Informationization: Education Rain R |
| 12 | course | June 2021 | Incorporating Maker-Centered Learning in Form |
| 13 | editorial | December 2009 | In CS education, educate the educators first |
| 14 | research-article | January 2020 | The Game and Integration between Online Edu |
| 15 | short-paper | November 2015 | Bringing the Innovations in Data Management |
| 16 | research-article | September 2020 | The Readiness of Principal and Educators in Im |
| 17 | technical-note | March 2008 | Security education: a roadmap to the future |
| 18 | poster | November 2018 | Integrating Computing Education to Teacher Ec |
| 19 | research-article | July 2019 | State Case Study of Computing Education Gove |
| 20 | research-article | August 2020 | SQL Education: A Systematic Mapping Study ar |
| 21 | research-article | September 2020 | Enhancing humanism values through higher ed |

Figure 3.10: Screenshot from MASSPR-Tool display the result of collecting scientific papers after applying a search query

We present an illustrative example of using the MASSPR tool. The first thing user should do is login into the software using the correct username and password Figure (3.9). This operation allows our tool to identify the user and load its profile to exploit it in the recommendation decisions. The second step is the configuration. The user should Write the search sentence or import a complete article as the search query. In addition, he can set the number of scientific paper want to download and the date interval of the searching process. The above-mentioned options are presented in the right of the figure (3.10). The result of crawling the web to find the relevant articles will display in a table as shown in the center of the figure (3.10). This table view includes some basic data of the collected articles such as article ID, Title, Publication Date, Citations, authors, abstract, references, and other data columns. The tool helps users to gain time of reading thousands of papers to select the most relevant for them and prepare a rich database of papers that cover the most papers in such domain. this database will be saved locally in the user devices for future use.

## 3.6 Results and Discussion

To evaluate the usefulness of our tool, we used approach based on the compare The results obtained by the MASPPR intelligent system with the ACM DL outcomes. In condition after applying the same query. To do so we collect a data-set of articles from the ACM DL concerning the subject of "Education" and "Covid-19". The data-set includes more than 1000 thousand scientific papers. the data columns of this data-set include all the information related to a published paper such as title, authors list, keywords, publication date, the published journal, abstract, references, citations, and many other data types. Then we execute the MASPPR algorithm to select the most relevant articles with the search query "Education + Covide-19". The Figures (3.11-3.13) presents a graph that includes the power values of the rest 15 article during the process of the MASPPR intelligent algorithm. in each iteration, the system recalculates the power of each article based on the above-mentioned formula and removes the articles that there power lower than the learning rate value. At the end, like is shown in the figure 3.14 the system selects the biggest 3 articles (in green circles) that have the top three pawer values and recommend them to the user. the blue circles represent that articles that are still relevant, but they are up the max number of articles required by the user. because in this experiment we set up the algorithm to select the top 3 papers. The red circles in the figure 3.14 represent all the papers that have been removed from the set of articles during the execution of the MASPPR algorithm.

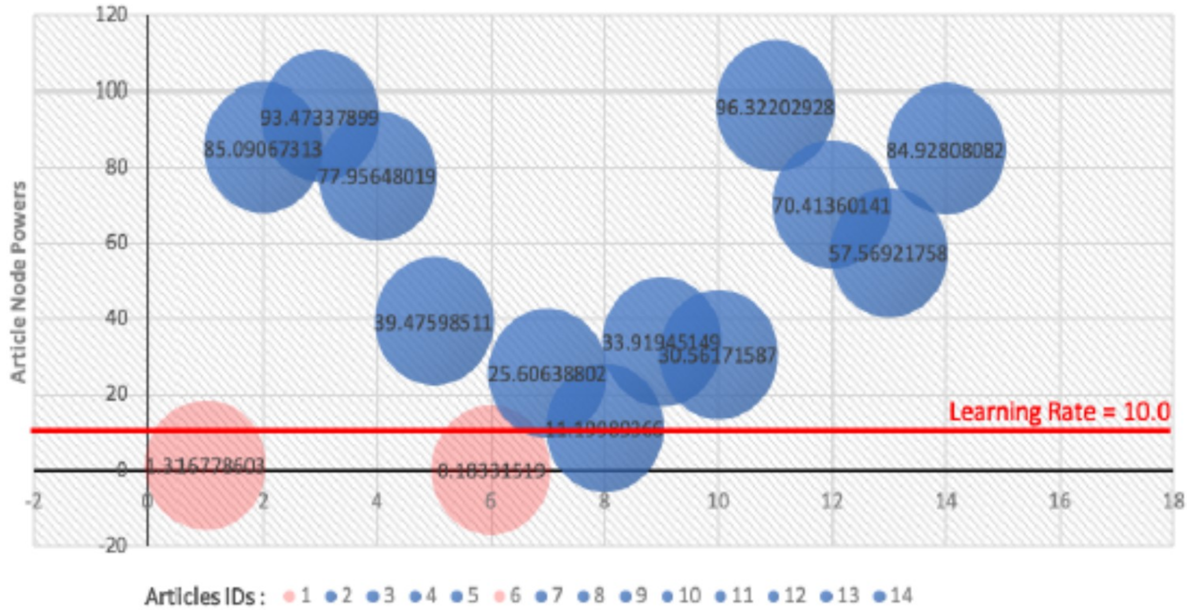



Figure 3.11: iteration Number = 1

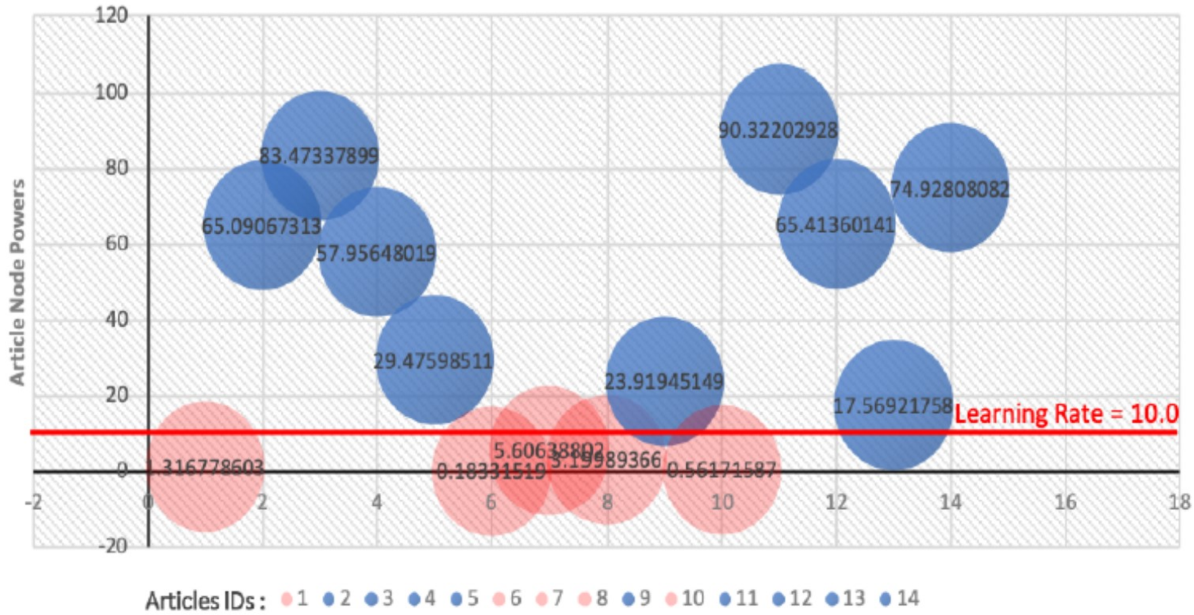



Figure 3.12: iteration Number = 2

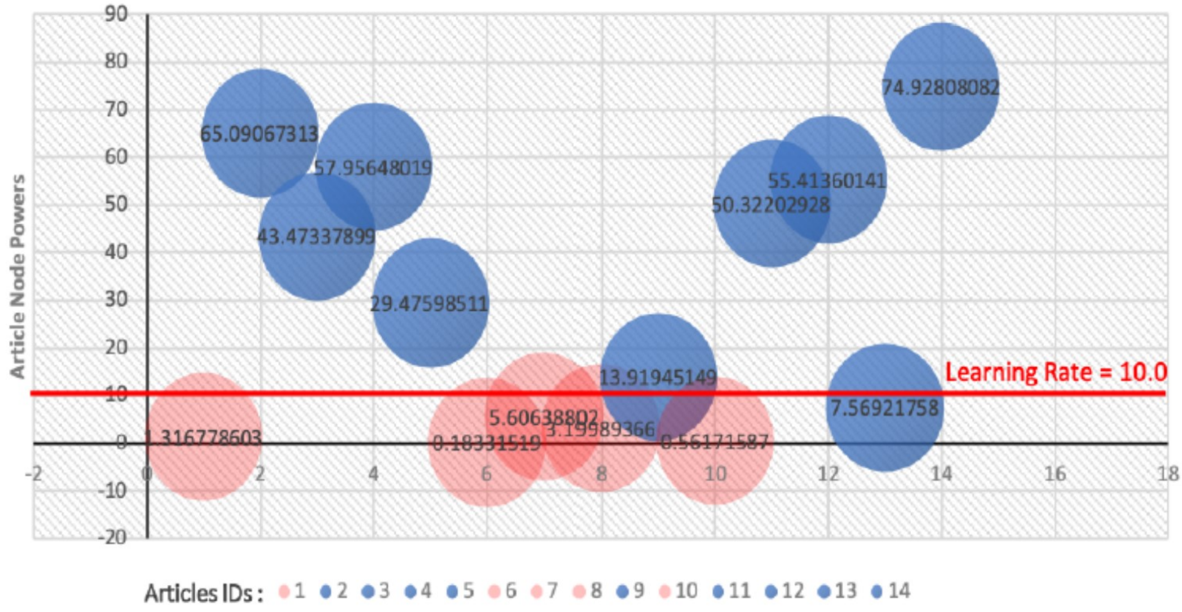



Figure 3.13: iteration Number = 3

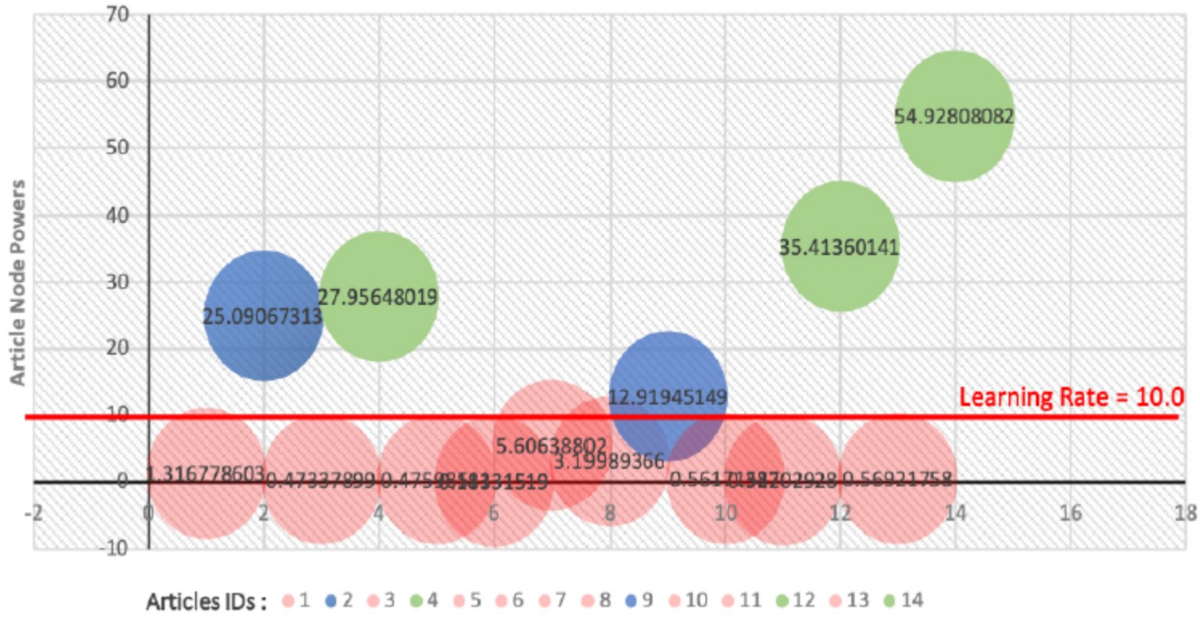



Figure 3.14: iteration Number = 50

We compared the results obtained with the results of ACM DL with the same research query (education+covid-19). We obtained very satisfactory results and were included in the articles recommended by our tool from the top 20 articles recommended by the ACM DL Library after applying the same query.

## 3.7 Conclusion

In this chapter, we implemented our intelligent, ontology-based instrument, the elements of which we outlined briefly and produced results and when compared to ACM DL results with the same query that turned out to be honorable results.

# CONCLUSION

This research aims to solve the problem faced by researchers in searching for relevant papers for their studies that consume time due to the huge amount of papers posted online that make searching difficult. Our work discloses that the ontology-based recommendation system, combined with recommendation techniques, is universally used to recommend context-aware resources can efficiently contribute to enhance the accuracy and quality of recommendations. Furthermore, it read and filters all the downloaded papers to recommend the most relevant papers for the user. It is based on an intelligent new mechanism proposed to enhance recommendations obtained by existing search engines.

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