Abstract. Nowadays, a huge amount of knowledge has been amassed in digital agriculture. This knowledge and know-how information are collected from various sources, hence the question is how to organise this knowledge so that it can be efficiently exploited. Although this knowledge about agriculture practices can be represented using ontology, rule-based expert systems, or knowledge model built from data mining processes, the scalability still remains an open issue. In this study, we propose a knowledge representation model, called an ontology-based knowledge map, which can collect knowledge from different sources, store it, and exploit either directly by stakeholders or as an input to the knowledge discovery process (Data Mining). The proposed model consists of two stages, 1) build an ontology as a knowledge base for a specific domain and data mining concepts, and 2) build the ontology-based knowledge map model for representing and storing the knowledge mined on the crop datasets. A framework of the proposed model has been implemented in agriculture domain. It is an efficient and scalable model, and it can be used as knowledge repository a digital agriculture.

Keywords: Ontology · Knowledge Map · Knowledge Management · Digital Agriculture.

1 Introduction

The knowledge from crop studies is turned into profitable decisions in digital farming only when it is efficiently managed. Farming knowledge can be created by the experience of farmers, by research studies in agronomy, or by analyses of data that has been collected for a number of years. In particular, the knowledge discovery in agricultural data is one of the most diverse, large, and dynamic in digital farming.

Moreover, one of the key challenges of knowledge management is the representation of the mined results, which are not consistent among different sources of knowledge. For example, consider two results that were obtained from two data mining studies, with the overall goal of predicting farming conditions of high crop yield of winter wheat. The concept high crop yield used in the two studies can be different, depending on the way authors define the range of high
Therefore, the overall insight may not be consistent to be used in the same system or to compare those results. This issue can also occur with input attributes used by different predictive models. In addition, the farming knowledge represented using an ontology is static and it is difficult to generalise to different regions, which have different farming conditions. The knowledge represented as rules in expert systems does not scale well and there is no way to refine the rules and it is also very difficult to check the coherence of all rules within a system. To summarise, while the knowledge mined from data mining processes is dynamic and flexible but its representation differs from one process to another. Some knowledge representation models are rules oriented while others are stored as vectors or trained models.

In this paper, we propose a scalable ontology-based knowledge map (OAK) model for representing, storing, managing and retrieving knowledge of any type. The main contribution of the model is to support data scientists and agronomists in managing and using mined knowledge for decision making with ease. The next section gives an overview of knowledge concepts and how to create knowledge in the agriculture domain. Section 3 describes in details the proposed OAK model, which includes definitions, architecture and its three main modules. Section 4 provides various experiments on the knowledge management system, which is based on OAK model. Finally, we conclude and give some future directions in Section 5.

2 Related Work

According to the Collins dictionary knowledge is an information and understanding about a subject, which a person has, or which all people have, while the Cambridge dictionary defines the knowledge as an information and understanding that you have in your mind. Knowledge Map (KMap) is defined as a spacial representation of information [22]. Knowledge maps are used extensively in enterprises to describe how, what or where to find useful knowledge within the enterprise organisations [6]. Knowledge graph (KG) is a set of pairs of knowledge \((V, E)\), where \(V\) is a set of nodes mapped to pieces of knowledge in the domain and \(E\) is a set of knowledge relations between two nodes. Ontology is a formal specification of the vocabulary to be used in specifying knowledge and the purpose of the ontology is to provide a uniform text-based knowledge representation, which is comprehensible by either human or machines [8]. The difference between these three concepts (KMap, KG, and ontology) is that ontology is used for formal and static knowledge, while KMaps and KG are used for handling more dynamic knowledge types, such as enterprise KMaps or Google Knowledge Graph [2].

In the following, discuss some relevant knowledge discovery processes in agriculture, particularly data mining, and review the knowledge representation and management gaps as a consequence of proliferation of big data analytics.

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1 https://www.collinsdictionary.com/dictionary/english/knowledge
2 https://developers.google.com/knowledge-graph
2.1 Knowledge Discovery in Agriculture

There are many ways in creating knowledge in any specific domain. The first method is to acquire knowledge manually by experts. The result of this approach is knowledge-base (known as taxonomy or ontology), or rule-based system (known as expert systems). Another way is to acquire knowledge automatically via a knowledge discovery process from structured or unstructured data. However, knowledge graphs are normally built from Wikipedia, Freebase, DBpedia and agriculture websites, such as, the AgriKG [4] and Cn-MAKG [5] systems.

During the last decade, the advances in digital agriculture have led to numerous significant studies on the application of data mining process to agricultural datasets. These datasets include including soil, weather, crop yield, and disease prediction. Moreover, the scope of research for data mining in agriculture is also diverse, including data construction as well as forecasting models. In this context, there are several computational soil studies, such as building datasets of soil profiles [21], monitoring soil characteristics under effects of other factors and crop yield [3], or using soil characteristics to predict other soil characteristics [23]. Another common application of knowledge mining in agriculture is crop yield prediction (e.g., predicting yield or wheat yield based on soil attributes, weather factors, and management factors [1, 12, 18]). Finally, the third common application of knowledge mining is the disease prediction or the protection plan (e.g., detecting nitrogen stress in early crop growth stage of corn fields [14], or detecting and classifying sugar beet diseases [7], etc.).

Data mining has four main categories of techniques; clustering, classification, regression, and association rule. To date, only classification and regression are widely used in digital agriculture. Usually, classification approaches are used to detect the disease (mostly based on the images processing techniques [7]), or to classify crop yield (as low, medium or high yield). Regression techniques are mainly used to predict crop yields based on different input attributes [1, 3]. Although the number of knowledge model types is not large, input and output attributes for forecasting models are totally different and diverse, and the number of agricultural attributes is very large. In addition, the idea of using KMaps for handling mined knowledge has been proposed in [9] and [10], however, it only proposed as a prototype for handling rules in data mining result. Therefore, the challenge of these knowledge types and KMaps approach for these knowledge types is that most of them are stored as pre-trained models or as computer software and their final results are mostly published as scientific papers or reports.

2.2 Methodology for Building Knowledge Map

There are many approaches for building knowledge maps (KMap). Most of these methodologies were dedicated to enterprise KMaps while several others are used to build specific domain of KMaps. For example, Bargent [2] proposed an 11-step methodology for building an enterprise KMap, which is a common strategy of software development life-cycle. Similarly, Kim et al.[8] proposed a 6-step methodology for capturing and representing organisational KMaps with
knowledge profiles and business processes, while Pei et al. [19] introduced a 7-step methodology to build an enterprise KMap for matrix organisations, including setting up a development team, analysis knowledge resources, definition of the business knowledge domain boundaries, determination of the structure and relationship for the KMap, selection of the development tools, identification of locations of knowledge items and drawing the initial KMap, and finally evaluation and updates of KMap.

Moreover, several studies have used ontology for building their knowledge maps. Lecocq [11] developed a 4-phase methodology with planning, collecting, mapping and validating phases based on an ontology for visually representing knowledge assets. In another study, Mansingh et al. [15] introduced a 3-stage methodology for building KMaps of medical-care processes; including creation of an ontology from the medical cases, creation of the process map with flowcharts and petri nets, and extraction of KMaps from instances of different medical-care processes (represented as medical files) by using vocabulary and relationships in that ontology. The method was tested in a healthcare organisation and was found to be suitable to build a KMap, which combines conceptual and process maps for medical-care processes.

To summarise, existing methodologies for building KMaps can be divided into two typical types; methods for building enterprise KMaps [2] [8] [13] [19] and methods for building conceptual KMaps [11] [15]. For building enterprise KMaps, although methodologies have different number of steps, they use basic stages: (1) identify the scope, domain of KMap and the develop team, (2) identify knowledge resources or materials, (3) identify knowledge in each knowledge item, (4) extract and build KMap, (5) evaluate, use, and update the KMap. For building conceptual KMaps or hybrid with conceptual maps, existing methodologies also have the same basic stages, however, one step in identifying knowledge resources or materials is to use an ontology as a conceptual framework for building KMap in subsequent stages. This step aims to locate the knowledge items in the final KMaps.

3 Ontology-based Knowledge Map Model

We propose an ontology-base knowledge map model for representing knowledge obtained from learning processes applied to agricultural data, from research articles, or from experts in the domain. Moreover, the model allows knowledge handling and exploitation in a flexible and scalable way. As illuminated in an example in Figure 1, the knowledge representation shows the results of a clustering model with 5 input attributes (Soil pH, seed rate, nitrogen, wheat name, and mean yield).

To implement the model and validate it experimentally, the system is designed and developed in two major phases: during the first phase we build an agriculture ontology and in the second phase we use the ontology vocabulary along with initial data schema (as in the data warehouse) to model the knowledge. Before going into the details, we need to define the key concepts be-
hind this model, which are knowledge representation, ontology, knowledge map model, concept, transformation, instance, state, relation, lexicon and hierarchy.

Fig. 1. Approach for Knowledge Map Model for Clustering.

**Definition 1.** A Knowledge representation \( K \) is defined by a set of four elements, containing instances \( I \), transformations \( T \), states \( S \), and relations \( R \):

\[
K = (I, T, S, R) \tag{1}
\]

**Definition 2.** An Ontology \( O \) is defined by a set of three elements, containing concepts \( C \), transformations \( T \), and relations \( R \):

\[
O = (C, T, R) \tag{2}
\]

**Definition 3.** A Knowledge Map Model \( KM \) is defined by a set containing five elements, \( C, I, T, S, \) and \( R \), which are corresponding sets of concept \( c \), instance \( i \), transformation \( t \), state \( s \) and relation \( r \).

\[
KM = (C, I, T, S, R) \tag{3}
\]

Where \( C \) is a set of concepts \( \{c\} \), and represents a set of entities or attributes of an entity within a domain and four data mining categories of results (clustering, classification, regression, and association rule).

\( T \) is a set of transformations \( \{t\} \), and represents a set of functions \( f(x) \) to transform the value of entities \( x \) from value range \( \mathbb{R}_x \) to value range \( \mathbb{R}_y \).

\( I \) is a set of instances \( \{i\} \), and represents a set of entities.

\( S \) is a set of states \( \{s\} \), and represents a set of real attributes of instances \( \{i\} \) when applying transformation \( \{t\} \).

\( R \) is a set of relations \( r \), and represents a set of relationships \( r \) between concept \( c_1 \) and concept \( c_2 \).
3.1 Architecture of Knowledge Map Model

As illustrated in Figure 2, the architecture of OAK consists of the following key components: (i) Knowledge Miner, (ii) Knowledge Wrapper and (iii) Knowledge Management System.

- **Knowledge Miner** is a key component, which is used to extract knowledge from data; this component can be a *Data Mining* or an *OLAP Analysis* module.
  - *Data Mining* refers to mining tools and techniques, which are used in analyzing datasets from various dimensions and perspectives, finding hidden knowledge and summarizing the identified relationships. These techniques are classification, clustering, regression, association rules.
  - *OLAP Analysis* refers to mining processes used in analyzing different dimensions of multidimensional data, which is collected from multiple data sources and stored in data warehouses.

- **Knowledge Wrapper** is the main module to transform the knowledge from the output of the *Knowledge Miner* module to the *Knowledge Management System* module to store them. This module collects the mining result, identify the type of the data mining task, data mining algorithms, list of agriculture concepts, correlative transformation functions, and states. Then, it generates the KMap representation before converting it into RDF turtles and import into the *Knowledge Management System*.

- **Knowledge Management System** is a graph database server, which supports RDF triple storage and SPARQL protocol for the queries. This module receives the domain knowledge from the pre-defined ontology, the mined knowledge representations from the *Knowledge Wrapper* module, and then store in the RDF Triple Storage as a set of RDF turtles.

In general, the proposed OAK model includes two knowledge layers. The first layer is the background knowledge about agriculture. This layer is defined as a
core MKap and it is built from a pre-defined agricultural ontology (mainly cropping knowledge in this project). This layer defines most of concepts (agricultural entities related to crop) in the KMaps and common relations between them. The second layer includes knowledge representations of data mining results, which are mined from cropping datasets by data mining algorithms (included in the Knowledge Miner module). These knowledge representations are integrated into the Knowledge Management System by the Knowledge Wrapper module.

### 3.2 Agriculture Ontology

In general, most ontologies describe classes (concepts), instances, attributes, and relations. Moreover, some ontologies also include restrictions, rules, axioms, and function terms. In our case, as a formal presentation of KMaps, we propose an ontology with the following components:

- **Concepts**: Concepts in the ontology include concepts in agriculture and concepts for representing four main tasks of data mining. For example, agriculture concepts have field, farmer, crop, organization, location, product, while data mining concepts have clustering, classification, regression, and association rule.

- **Transformations**: They are pre-defined transformation functions of agriculture concepts and existing data mining techniques for four main tasks of data mining.

- **Relations**: ways in which concepts (and then instances) can be related to others. They are defined as the $\mathbb{R}$ set in definitions.

At this stage, we propose an agricultural ontology AgriOnt for the purpose of using it in the OAK model. The agricultural ontology contains 4 sub-domains: agriculture, Internet-of-Thing (IoT), geographical, and the business sub-domain (Figure 3). In addition, the ontology is also added concepts in data mining domain as shown in Figure 4. These concepts and relations will be knowledge frameworks to transform mined knowledge from data mining to knowledge representations and import them into the knowledge maps.

| Figure                                      | Core | with Transformations | with Geo-data |
|----------------------------------------------|------|----------------------|---------------|
| Axiom                                        | 7,947| 10,484               | 13,917        |
| Logical axiom count                          | 3,782| 5,194                | 7,892         |
| Declaration axioms                           | 1,796| 2,218                | 2,460         |
| Class count                                  | 361  | 361                  | 361           |
| Object property count                        | 90   | 90                   | 90            |
| Data property count                          | 156  | 156                  | 156           |
| Individual count                             | 1,183| 1,605                | 1,847         |
After building a knowledge hierarchy, the ontology not only provides an overview of the agriculture domain but also describes agricultural concepts, and life cycles between seeds, plants, harvesting, transportation, and consumption. It also gives the relationships between agricultural concepts and related concepts, such as weather, soil conditions, fertilizers, farm descriptions. In addition, this ontology also includes data mining concepts, such as classification, clustering, regression, and association rule. These concepts combined with agricultural concepts that are used to represent mined knowledge. In fact, this ontology has 361 classes and over 7,947 axioms related to agriculture (as shown in Table 1 and partly presented in [16]). As result, the AgriOnt ontology can be used as the core ontology to build the knowledge maps for agriculture. Moreover, this ontology with agricultural hierarchy can help to integrate available resources to build larger and more precise knowledge maps in agriculture domain.

3.3 Knowledge Management System

The knowledge consumption is handled in the Knowledge Wrapper module. This wrapper transforms the mined knowledge to the Knowledge Maps layer. The Knowledge Maps layer stores and indexes RDF-based data. The Knowledge Maps layer provides the Data Access interfaces for query processing SPARQL engine. The SPARQL engine enables the application developers to query data via a SPARQL Endpoint or a SPARQL-based application in the Application layer respectively. The SPARQL Endpoint serves one-shot queries using an extension of SPARQL 1.1 query language.
In our approach, we use Apache Jena\(^3\) for SPARQL Engine and Fuseki\(^4\) for SPARQL Endpoint. Both Apache Jena and Fuseki are free and open source. Fuseki is an HTTP interface to RDF data and it supports SPARQL for querying and updating data.

### 3.4 Knowledge Wrapper

The procedure for mapping mined knowledge into a knowledge representation in the ontology-based knowledge map is defined in the Knowledge Wrapper module. The Knowledge Wrapper module is the main module to transform the mined knowledge into a knowledge representation \(k\) (as defined by \(k = (\{i\}, \{t\}, \{s\}, \{r\})\) in Definition 1, Section 3) before converting into RDF triples and import them into the RDF Triple storage. This module has six steps (Figure 6):

- **Step 1, Identify model**: Select data mining pattern based on the data mining algorithm and generate the data mining instances (such as classification, clustering, clustering, and association rule instances for the corresponding data mining tasks) and link to the data mining algorithm as the transformation objects of the data mining instances.

- **Step 2, Identify concepts**: Identify agricultural concepts in mining results and locate them in the ontology. Basically, these concepts occur in the mined results as input features and predicting features, for example, SoilPH, SeedRate, Nitrogen, Wheat, MeanYield.

- **Step 3, Generate instances**: Generate agricultural instances of each located concept and link them to data mining instances (in Step 1) based on the framework of data mining tasks.

\(^3\) https://jena.apache.org/index.html
\(^4\) https://jena.apache.org/documentation/fuseki2/
Fig. 5. A screenshot of Agricultural Ontology on Protege

- **Step 4, Identify transformations**: Identify transformations of each concept in the mining results, locate them in the ontology part of the KMap, then link them to the agricultural instances (in **Step 3**).
- **Step 5, Generate states**: Identify states of each concept in the mining results, generate states and link to instances (in **Step 3**) in the knowledge representation.
- **Step 6, Generate turtles**: Transform the knowledge representation into RDF turtles and import them into the RDF triple storage.

In fact, the set of instances \( \{i\} \) is created in Step 1 and Step 3, while the set of transformations \( \{i\} \) is created in Step 1 and Step 4. The set of states \( \{s\} \) is generated in Step 5, however, not all knowledge representations have sets of states. For example, in the model to predict crop yield, the input values only occur when the model is executed. Therefore, the set of states for this knowledge representation is nearly none. Finally, set of relations \( \{i\} \) is based on relation \( \text{isA}, \text{hasTransformation}, \text{hasState}, \text{hasCondition}, \text{and predicts} \).

4 Experimental Results

Firstly, we have set up a SPARQL Server as a knowledge management system (cf. Section 3.3) with Apache Jena and Fuseki library. The system has also created
a new knowledge map with a pre-defined ontology (as described in Section 3.2) and several samples of knowledge representations, which are created manually by Protege tool (as shown in Figure 5). The SPARQL Endpoint can be accessed at http://localhost:3030/manage.html on local machine for query.

Basically, SPARQL queries can be run on the Endpoint with a web interface. Figure 7 shows the results for the query ”What are conditions and the target attribute of the knowledge model Regressor_004?” The SPARQL query for this question is shown below:

```
PREFIX AgriOnt: <http://www.ucd.ie/consus/AgriOnt#>
PREFIX AgriKMap: <http://www.ucd.ie/consus/AgriKMap#>
SELECT ?predicate1 ?object1 ?predicate2 ?object2
WHERE {
    AgriKMap:Regressor_004 ?predicate1 ?object1 .
    ?object1 ?predicate2 ?object2 .
    ?object1 ?predicate2 ?object2 .
}
```

In this example, the mined knowledge for predicting soil pH [17] can be represented as a knowledge representation Regressor_004 in the system. Inputs of the model are pH information and the output of the model is also the pH value (concept SoilPH), however, they used different transformations. Specifically, input features are calculated as pH_{min}, pH_{max}, and pH_{avg} (three different transformations of SoilPH in the system) of nearest neighbour fields, while the output feature is predicted as the original pH value of the field (these conditions are defined as Soil_001, Soil_002, Soil_003 and Soil_000 instance, as shown in Figure 7).
In addition, the knowledge management system based on the OAK model can be benefit for both data scientists and agronomists. Data scientists can have queries about potential transformations of agriculture attribute $c_x$ (for example, Soil pH or Temperature), and these queries can be implemented by a SPARQL query as below:

```
PREFIX AgriOnt: <http://www.ucd.ie/consus/AgriOnt#>
PREFIX AgriKMap: <http://www.ucd.ie/consus/AgriKMap#>
SELECT ?subject ?predicate ?object
WHERE {
  ?subject AgriOnt:transformationOf AgriOnt:SoilPH .
  ?subject ?predicate ?object
}
```

For agronomists and also farmers, they can have queries about potential knowledge models or attributes to predict an attribute, such as crop yield. The SPARQL query returns all potential knowledge models that are used to predict CropYield as below:

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX AgriOnt: <http://www.ucd.ie/consus/AgriOnt#>
PREFIX AgriKMap: <http://www.ucd.ie/consus/AgriKMap#>
SELECT ?subject ?predicate ?object
WHERE {
  ?subject ?predicate ?object .
  ?subject AgriOnt:predicts ?object2 .
}
```
Similarly, agronomists also can have queries for a specific state during farming, such as how to get a high crop yield or how to identify the Leaf brown spot disease. For example, the below query returns a knowledge representation Classifier_016, which is study of Santanu Phadikar [20] for detecting 4 rices diseases, including Leaf brown spot, Rice blast, Sheath rot, and Bacterial blight. In which, Sheath rot is one of four predicting states of the model. The query also provides all information related to input attributes, prediction method and evaluation information (Figure 8).

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX AgriOnt: <http://www.ucd.ie/consus/AgriOnt#>
PREFIX AgriKMap: <http://www.ucd.ie/consus/AgriKMap#>
SELECT ?subject1 ?predicate2 ?object2
WHERE {
  ?subject1 ?predicate1 ?object1 .
  ?object1 AgriOnt:hasState AgriOnt:SheathRot .
  ?subject1 ?predicate2 ?object2 .
}
LIMIT 100
```

Fig. 8. Returns of SPARQL query for Sheath rot disease
5 Conclusion

In this paper, we present an architecture for the OAK - an ontology-based knowledge map model to represent mined knowledge from data mining tasks in digital agriculture. The architecture includes Knowledge Miner, Knowledge Wrapper, Knowledge Management modules based on a pre-defined ontology. We have also built an agricultural ontology to provide the domain knowledge in agriculture and a knowledge management system to store knowledge representations and support the knowledge retrieval efficiently.

With the proposed ontology-based knowledge map model, the knowledge management system based on this model is a promised architecture for handling mined knowledge in agriculture as well as other domains. As result, we plan to import more knowledge items in the digital agriculture domain into the knowledge management system for retrieval. Moreover, the knowledge management system also supports a knowledge browser function as a further method to access knowledge for both data scientists and agronomists.

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