Semantic of Cloud Computing services for Time Series workflow

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Abstract—
Time series (TS) are present in many fields of knowledge, research, and engineering. The processing and analysis of TS are essential in order to extract knowledge from the data and to tackle forecasting or predictive maintenance tasks among others. The modeling of TS is a challenging task, requiring high statistical expertise as well as outstanding knowledge about the application of Data Mining (DM) and Machine Learning (ML) methods. The overall work with TS is not limited to the linear application of several techniques, but is composed of an open workflow of methods and tests. These workflow, developed mainly on programming languages, are complicated to execute and run effectively on different systems, including Cloud Computing (CC) environments. The adoption of CC can facilitate the integration and portability of services allowing to adopt solutions towards services Internet Technologies (IT) industrialization. The definition and description of workflow services for TS open up a new set of possibilities regarding the reduction of complexity in the deployment of this type of issues in CC environments. In this sense, we have designed an effective proposal based on semantic modeling (or vocabulary) that provides the full description of workflow for Time Series modeling as a CC service. Our proposal includes a broad spectrum of the most extended operations, accommodating any workflow applied to classification, regression, or clustering problems for Time Series, as well as including evaluation measures, information, tests, or machine learning algorithms among others.

Index Terms—Time Series, Data Mining, workflow, Cloud Computing, Services Description, Service Industrialization, Linked Data, Semantic Web Services

1 INTRODUCTION

Forecasting of weather conditions, the estimation of the value of stock market shares, or the detection of anomalies on industrial processes among others, are part of the set fields where the TS data analysis plays a basic role to tackle knowledge extraction.

Time series is a sequence or sequences of data spaced out in time; events, activities, or devices continuously generate information that is temporally logged and stored for real-time or post-processed study. The work with TS is one of the fastest growing at the moment, due to the proliferation of the so-called IoT [1], for instance. Increasingly in interest, the use of mobile devices, autonomous vehicles, modern agriculture, or intelligent machines, will produce a huge amount of information in the coming years and a significant percentage of this information will be in the form of TS data [2].

At the present time, when CC has practically been integrated in a totally transparent way in our relationship with Information Technologies (IT) and Internet, the activities related to data analysis are incrementally being added to the spectrum of services offered by the CC platforms and providers. Analysis and study of TS will need to be processed as CC services following the NIST [3] recommendations such as flexibility, scalability, portability, and security.

The rise of CC in parallel with the increase in computing capability has led to the deployment of tools and platforms for data mining and data analysis. Both offer a wide range of methods, functions and algorithms to perform data processing at all scales, either from the desktop [4], [5], large clusters [6], [7], [8] or from service platforms in CC [9].

Within the area of DM, these CC providers and platforms offer barely TS services and methods in a catalog of services [9]. This means having to implement specific methods and algorithms for working with TS on each provider platform or to migrate all the source code developed in a specific programming language and to ensure the entire service deployment will work properly. TS modeling can be a highly complex and it supposes a non-linear analysis tasks [10] including a set of methods of the application of DM and ML techniques [11], models, evaluations of performance or precision measurements, among other, that can be seen as a workflow of tasks.

The services of TS analysis along CC service providers address a lack of integration from heterogeneous and non-standardized cloud computing platforms. When migrating services from one CC provider to another, the ideal solution would be to harmonized the description of services and workflow related to TS on CC deployments, abstracting the programming language or the architecture of deployment. This would allow the interoperability of these services between providers to be exploited more efficiently and offer all the scalability and flexibility advantages provided by the CC paradigm. With this idea we pursue the industrialization of IT services through pre-designed and pre-configured solutions that are highly automated and repeatable, scalable and reliable, by meeting the needs of users or organizations.

The aim of this paper is to propose a definition of services for TS workflow in CC environments based on semantic technology, according to the Linked Data [12]
Finally, the conclusions of the work and the proposals for workflow modeling with TS is not taken into account being an incremental manner, due to the rise of IoT environments and knowledge extraction from data sources in real time or offline. In this way, an important part of the work carried out with time series has been developed within distinct fields such as business, economics, stock market, environmental sciences, industrial monitoring, or engineering among others [15], [16], [17].

The analysis and modeling of TS is a complex task that includes the application of various operations, techniques and algorithms. This procedure can be seen as a workflow, covering a large number of methods and techniques to apply and focused on solving TS problems [18].

The analysis of the time series has been studied in depth and there is no single criterion that establishes which is the procedure to be carried out for the workflow in this type of problem. There are different methodologies to tackle the problem of modelling and the approach to TS resolution. The most widely used proposal is the Box-Jenkins methodology [19]. This methodology can be considered as linear workflow. Box-Jenkins is used in the construction process of the ARIMA [20] model for the TS covering aspects such as identification, estimation, error-testing and application of methods and modelling [21]. Focusing on modelling, techniques related to ARIMA, such as AR, MA or ARMA [22], are also used as part of the TS workflow process. The modelling of TS from a non-linear perspective has been approached with the use of ANN [23], bi-linear model, TAR or ARCH [24]. Other modelling techniques based on DM and ML have been proposed including Random Forest [25], Support Vector Machine [26], Neural Networks [23], or the more modern Deep Learning one as in [27]. The TS analysis also includes a comprehensive set of extract, transform, load (ETL) data processing tasks [28].

TODO: add missing [REF] and figures in the document.

For the resolution of this type of analysis, programming languages and tools have been widely used, in addition to DM platforms [29]. These utilities include all the required components and functions for the relative TS workflow. Languages such as R (with its task-view for TS) [30] or Python (TS-specific libraries) [31], software packages such as SAS [REF] or MathLab [REF] and DM environments such as KNIME [32] or WEKA [4] offer the tools to make effective the work with TS. In all of them, it is possible to design a workflow where you can specify the application of operations, visualize the results, validate errors and apply multiple algorithms for the modelling and subsequent forecasting, classification or clustering [33].

Most traditional time series analysis tools are designed to work with desktop computers and are not ready to be used in CC environments. Leveraging the computing capabilities of organizations, part of that vast set of resources and infrastructure are being allocated to DM and ML as on-demand CC services [9]. TS analysis is no exception and more and more CC providers are including specific functions and algorithms for working with TS services in their catalog [34]. Currently, there is a growing demand for services that allow creating workflow to be deployed over CC, such as TS [35], [36]. These workflow are very interesting because of their scalable character existing a clear need to move much of the data processing to cloud platforms, abstracting the underlying computing infrastructure and scalability needs, both of which will be assured [37], [38].

One of the main problems of CC services is the lack of a consistent and standardized definition of these services among the different CC providers and it has been widely studied [39], [40]. This happens in the same way with the description of workflow and experimentation with data in CC [39], [40]. This happens in the same way with the description of workflow and experimentation with data in CC in the analysis of TS. The portability of services and the ability to abstract the underlying infrastructure makes it necessary to validate this type of problem on CC platforms [41].

Workflow modeling for DM experimentation is considered in [42], [43] performing workflow as CC services giving the user the ability to deploy a work of experimentation in an integral way. Several approaches manage the problem of the description of workflow dealing with ontology-based such us RDF or Turtle [44]. Those languages for workflow definition have been discussed in [45] and [46].

The definition and description of generic CC services that integrate multiple aspects of experimental work for DM have been worked from the scope of the Linked Data proposal. Research papers such as DMOP [47]. Exposé [48], dmcc [14] or MLSchema [49] are examples of languages proposals for the definition of generic data mining services and workflow, related to ML. These provide an adequate definition of services using a highly flexible definition language and linked to the natural development of the CC.

Most of the proposals allow the development of experimental analysis, including part of the usual workflow with data processing and algorithms [50]. In these works the workflow modeling with TS is not taken into account being a fundamental element for the integration of these services within CC platforms [51]. These types of problems need to bring together the different techniques and algorithms of TS modeling, pre-processing [22], performance measurements [REF], visualization [REF], or predictive models among
others. In our work, a proposal of workflow modeling for TS in CC has been developed, which allows to tackle the work with the TS experimentation and modeling using Linked Data recommendation on services description in CC platforms.

3 TIME SERIES SERVICE DESCRIPTION

Time Series modeling is a challenging task that integrates different actions following a dynamic workflow. In this work a complete proposal for workflow modeling with TS in CC has been made. The proposed schema is called tswf-schema and has been developed using a semantic language based on ontology, following the Linked Data guidelines for the definition and description of concepts, entities and relationships to other schemes. A complete diagram has been defined allowing any workflow with TS to be modeled, as can be seen in the section on ??, in which several examples of working with time series are developed and modeled using tswf-schema.

The scheme is divided into several parts that facilitate its integration and modularity, these are: data pre-processing, data visualization, functions for information analysis, work with seasonality analysis, predictive model selection, learning problem information, data entry, and performance evaluation measures, among others. Each of these parts is developed in detail throughout this section. In figure ?? you can see the general diagram of the flow rate modeling with time series that has been designed. For reasons of space, the complete scheme has not been displayed, given its size, so that each of the major container classes has been shown. Following the Linked Data specification, other vocabularies have been used from other schemes, completing and broadening the definition of the scheme. The scheme provided by MLSchema [49] and dmcc-schema [14] has been used as base for the workflow of experimentation with TS, in addition to other vocabularies such as SKOS [53] or schema.org [54] among others.

For the definition of workflow modeling has been taken into account a high volume of research papers and books related to TS modeling and analysis. For the container classes and other parts of the scheme, research related to the area has been reviewed, along with actual TS analysis work from various sources such as [11] [55] [56]. This has made it possible to extract a large part of the operations and methods used to model TS, also from multiple knowledge domains. In the proposal developed in tswf-schema we have integrated the greatest number of functionalities, together with the most common ones during the workflow process with TS. It also comprises widespread modeling such as the Box-Jenkins [19] methodology as well as workflow-based experimentation for processing DM problems and ML applied to TS [57] [58].

The tswf-schema contains all key elements in the description of cloud computing services, such as interaction points, prices, instances or SLAs, among others, and serves as a complement to the integration of a workflow with time series as a Service on CC platforms. This means that it allows you to have the complete description of CC services, both from a functional and a business point of view.

In the following subsections, all the main components of the tswf-schema definition are detailed:

Pre-processing. Part of the analysis and work with TS requires operations on the data, where they apply transformations, reductions, cleaning, or imputations among others. In the diagram in figure ?? you can see all the elements most commonly used in data level time series processing. It has basically been segmented into various parts, such as imputation, outliers, spectral analysis, scaling, noise reduction or smoothing. Each of the sub-parts contains several of the functionalities that have been considered the most commonly used in the processing of these types of data, according to the work of [52].

Analysis of the information and analysis of seasonality. Most of the statistical studies with TS are based on the Box-Jenkins methodology [19], where a series of studies on the data of the time series is applied to check the trend, seasonality among others, as well as different statistical tests necessary to correctly identify the time series. As shown in figures ?? and ?? they have been divided into two parts, on the one hand, the analysis of the information, which includes correlation, seasonality and trend tests. On the other hand, it also includes statistical tests, integrating stationarity, normality, randomness or non-linearity among others.

Evaluation measures. The output of the analysis workflow of a TS can be identified according to the TS study problem in question. Four main groups of measures have
been considered, related to those most used in TS problems, such as classification, similarity measurements, precision of the forecast, performance of the clustering, or analysis of the residues. Classification measures such as F1-Score, ROC, or matrix confusion have been taken into account. For similarity measures, others such as DTW, Edit Distance, or Jaccard have been implemented, as they are common in problems of this type. As regards the Error measures, which identify the quality of the forecast adjustment, all the measures considered in the work have been included. If the problem being addressed is related to time series clustering, different measures such as APN, AD/ADM or Silhouette W have been taken into account. Figure 5 details the set of evaluation measures that have been included in tswf-schema.

**Predictive model.** When instantiating a model that tries to fit the data of the TS, a multitude of algorithms and statistical methods can be applied. In our work we have integrated the algorithms and methods most commonly used in this area of TS data analysis. From widespread statistical methods such as ARIMA or variants of it (ARIMA, SARIMA, ARIMAX, etc.), as well as others such as ETS among others. Regression analysis has also been implemented with methods related to time series considered in studies, such as AR, LASSO or MARS among others. Finally, an important part of Machine Learning methods has been considered, mainly from studies. These algorithms include the application of techniques based on Neural Networks, Random Forest or SVM among the most outstanding. The complete diagram of the methods and algorithms included in tswf-schema can be seen in figure 5.

**Visualization of the data.** One part of the work is to perform repeated visualizations of the data to assess the state of the data and to use different plot analyses to better understand the shape of the data. This allows to observe some of the visual information such as decomposition, differentiation or STL plots. Figure 7 implements the set of visualizations available.

**Workflow.** The study of data generally does not follow a linear work scheme as indicated with this particular type of data, so that the data engineer or data scientist generates different flows of operations with which to compose the work during the analysis. To facilitate this task in tswf-schema, all operations and tasks that are performed can be composed as a linear or nonlinear sequence. If we think at a high level, this feature is what will provide the CC service for TS with the necessary functionality to visually compose (as building blocks) each operation or task to be performed at each time to produce a complete analysis. In figure X can be seen how this functionality intrinsic to tswf-schema serves to manage the flow of operations contained in the scheme.
4 Deploying Time Series Services

Once all the components of tswf-schema have been defined in the previous section, it is necessary to present a set of examples that highlight the potential of the scheme designed to describe TS workflows.

To address the presentation of these cases, two models will be used, on the one hand a) the straightforward transcription of examples proposed in a programming language into tswf-schema, putting the value on the ease of translating any TS-based study into a semantic agnostic model ready to be ported, deployed or executed on CC providers, and b) the modelling of a cloud service with key components of the service, so that a CC service is specified and it is ready to be part of a CC provider’s catalogue. For the examples we will use R and Python language, since they are one of the most extended languages and for the transcription of those example codes to the tswf-schema scheme we will use json-ld.

In order to make the process of developing a CC service based on TS more comprehensible, the figure 8 shows the different elements that make up a CC service. This figure shows several aspects related to the definition of the service management logic, more closely linked to the definition of CC, and on the other hand the description of the service functionality itself, in this case, a workflow with time series that runs as a service within a CC provider’s service catalogue.

4.1 Baseline of the structure of a TS workflow

The general minimum structure for designing and instantiating a TS analysis using tswf-schema can be seen in the listing 1, according to the figure 8 that outlines the overall diagram of the scheme. This skeleton contains the basic components that will be instantiated to show a functional example of the description of a workflow with TS, where in line 2-3 is established which will be the context of vocabulary used for the definition in json-ld, from line 6 to 10 are added the different operations of pre-processing of input data and various studies on them. Then in lines 11 and 12 are stated the methods that will be used to create the models and from line 15 the workflow information output. Each of the skeleton components is detailed in the following sections.

Listing 1. Skeleton of the component instantiation in json-ld

```json
"@context": {
...
"tswf": "http://dicits.ugr.es/linkeddata/tswf-schema/"
},
...
"tswf:hasInput": {
"tswf:hasPlot": {...},
"tswf:hasInformationAnalysis": {...},
"tswf:hasStationaryAnalysis": {...}
},
"tswf:performs": {
"tswf:hasTSAnalysis": {...},
...
"tswf:hasOutput": {
...

```

4.2 A model of TS analysis

For this use case we will use an example of an actual time series analysis, implemented in the R language. This example consists of a series of basic steps that reproduce the modeling of a simple TS example. This workflow can be seen visually in the figure 9.

The full code in R and Python of the workflow implementation can be found in the scheme repository [68]. In the description of the use case, we represent some parts of the modeling as a service, so we can compare the R-language code transcription to the tswf-schema scheme with json-ld as a semantic description language. This is not to replace one language with another, but with tswf-schema a complete description of a high level workflow is provided, abstracting the programming support, the platform or the computing environment. One of the advantages of using semantic models is that you can indicate the level of detail you want in each defined aspect. This is more expressive and less complex to understand, leaving more core aspects to the implementation of the underlying system that manages the schema, such as the default settings.

One of the advantages of using semantic description technologies to define services or functions is that you can indicate the level of detail you want in each defined aspect. This is more expressive and less complex to understand, leaving more core aspects to the implementation of the underlying system that manages the schema, such as the default settings.

4.2.1 TS Analysis: Workflow information and description

The definition of services in general terms requires a minimum of basic information describing what is being implemented. In our case, the first step to define the workflow instantiation with tswf-schema is the description of the analysis, through the main class TSAnalysis. With TSAnalysis and its properties all the attributes considered key in the definition of what is going to be deployed are declared so that it can
be described in the most efficient way possible and with a friction-less integration in catalogs or marketplace of services in Cloud Computing. Aspects related to the automatic discovery of services for CC would be defined from this class. For space reasons not all attributes of TSAnalysis will be exposed, so only some basic ones are shown in the listing 2.

Listing 2. Definition of the basic information of time series analysis

```json
"@context": {  
  "tswf": "http://dicits.ugr.es/linkeddatalas/../../../tswf-schema/"  
},  
"@id": "http://dicits.ugr.es/tswf-marketplace/#TS_eb09t74",  
"@type": "tswf:TSAnalysis",  
"tswf:name": "TS Analysis base with code TS_eb09t74",  
"tswf:description": "This is an example of TS an.",  
"tswf:author": "This is an example of TS an.",  
"tswf:dateCreated": "2020-09-01 10:30:00",  
"tswf:version": "Test version 1.0",  
"tswf:codeRepository": {  
  "@type": "tswf:url",  
  "@value": "https://"  
}  
"tswf:hasInput": ...
```

In the first lines (lines 1 to 3) the context of the overall TSAnalysis description is declared in which tswf-schema will be used. The context allows applications to use a set of terms to communicate with one another more efficiently, but without losing accuracy. Then, each instance of TSAnalysis created with tswf-schema must be marked with an identifier that uniquely relates this workflow, for example, within a particular catalog, for which id is specified (line 4). The @type property indicates that all the remaining content corresponds to a TSAnalysys and subsequently part of its attributes are declared (lines from 5 to 13), such as the TS name, description of the workflow, or the repository where the code of the described service will be hosted, to take the description of the flow to execute it (lines 11-14). The rest of the properties of the workflow components are instantiated in the following subsections (from line 15, with "tswf:hasInput", "tswf:hasOutput", etc. as described within figure X).

4.2.2 Data input

To perform the ingestion of the data of a time series, basically in the R language the data can be loaded from different sources, such as CSV format for example. In CC environments or other computing platforms it is possible that data can come from databases, TS databases, or even data steaming services. In this way, just as R or Python supports data ingest from multiple sources, tswf-schema has the possibility to include very diverse data sources. For the data input instantiating it is necessary to at least define the data source, the source type and the fields that will be used during the whole analysis process. In the listing

```json
3 a simple instantiation of the data entry is shown, where over the line number 2 is indicated the type of entry (tswf:Data), the type of source (tswf:CSVFile in this case) in lines 3-4 and where physically are the data by means of the property tswf:src (line 5). Then, with tswf:fields the features and fields of the data source are set within the lines 6-12.

Listing 3. Instantiation of the data entry source and its parameterization

```json
...
"tswf:hasInput": {  
  "@type": "tswf:Data",  
  "tswf:source": {  
    "@type": "tswf:CSVFile",  
    "tswf:src": "http://dicits.ugr.es/linkeddatalas/lakehuron.csv",  
    "tswf:fields": {  
      "@set": [  
        {"@value": "Year",  
         "@type": "tswf:integer"},  
        {"@value": "Level",  
         "@type": "tswf:integer"}  
      ]  
    }  
  }  
}
```

The transformation of the initial data intake part into tswf-schema is done at a higher level, since semantically each operation is labeled with its properties. This allows not having to define in advance each detail of the parameterization (or indeed the application of the TS type), so that this complexity can be left to the underlying system or platform as the service responsible for making these tweaks.

4.2.3 Preliminary exploratory analysis

A basic part of the analysis of TS data is exploratory data analysis where the data can be plotted, checked for patterns or trends, verified for seasonality or the presence of cycles, among others. In the example, we are dealing with, through the input data we make several key charts to visually understand the problem. We consider for instance the PACF (Partial Autocorrelation Function), ACF (Autocorrelation Function), STL (Seasonal and Trend decomposition using Loess) as well as a visual representation of the data.

The graphical representation of the input data is done from the @tswf:hasPlot property. In tswf-schema there is a set of possible definitions of the most commonly used charts and graphs within TS analysis as shown in listing 4. Note that the level of detail selected to instantiate these types of charts does not include parameterization except in @tswf:PlotPACF, this is because the internal implementation will be in charge of using the correct visualization with the default parameters of each chart type for the input data. On the other hand, for tswf:plotPACF a lag parameter (tswf:parameters) and its specific value have been indicated (lines from 6 to 12).

Listing 4. Set of diagrams/Charts that are deployed

```json
...
"tswf:hasPlot":{  
  "@type": "tswf:TSPlot",  
  "@set": [  
    {"@type": "tswf:PlotSTL"},  
    {"@type": "tswf:PlotACF"},  
    {"@type": "tswf:PlotPACF"},  
    "tswf:parameters": {  
      "@set": [  
        {"tswf:name":"lag", "@value": 10}  
      ]  
    }  
  ]  
}
```

Listing 5. TS information analysis

```json
...
"tswf:hasInformationAnalysis": {  
```

Fig. 10. Diagram of the components and operations of a simple TS analysis use case using tswf-schema.
Further on, in the listings [6] and [8] are shown how it is possible to add different studies used in the analysis, such as Information Analysis, or Stationary Analysis. For both types of studies, following the scheme shown in figures [3] and [5] it is possible to include their corresponding tests and operations. For the analysis of the information, as shown in list [5] four basic studies have been added in the work with TS (lines 4 to 8). In the same way as with the descriptions of the charts, we have taken all the default parameters for this example. On the other hand, in the study of stationarity analysis shown in list [6] four basic tests have been added (lines 4 to 8).

4.2.4 Predictive model and evaluation measures

Once the exploratory analysis is done, the selection and adjustment of the model is performed. The selection of the best model depends on the accuracy of the forecast (tswf:ForecastAccuracy) and finally, with the models generated in the previous stage through the property tswf:performs (in this instance AR, ARIMA and SVN).

Finally, as part of the explicit output of the workflow, using the tswf:hasOutput property, it is possible to indicate what kind of additional information can be analyzed as a result of the full process (listing [7], line 2). This has included in the output of the workflow the prediction function, which is called to return the results on how is the forecasting on different horizons, by giving the user of different measures to evaluate the performance of the forecasts, for example (see figure [5]). In the listing [7], lines 5-10 we have chosen to include two measures (RMSE and MSE) for the evaluation (tswf:EvaluationMeasures) with which you can verify the accuracy of the forecast (tswf:ForecastAccuracy), made with the models generated in the previous stage through the property tswf:performs (in this instance AR, ARIMA and SVN).

4.3 A CC service for TS

The TS example provided in the section [3] is defining a workflow as if we were doing it in a programming language like R or Python, but using json-ld as a description language. With tswf-schema it is possible to package TS workflows and make them portable between different computing platforms by reading the description and operating each high-level component on an underlying platform or by using a Broker to decide which SVM or ARIMA implementation at the low-level will be used to process a particular element. This gives an idea of the potential of using this type of semantic technology to tackle the deployment of services in CC. In this manner for this use case we want to put the value of using this type of semantic technology to tackle the deployment of services in CC. In this manner for this use case we want to put the value of using this type of semantic technology to tackle the deployment of services in CC.

Following the principles of Linked Data for semantic data, we will reuse another scheme called dmcc-schema [29] that allows unifying all the basic aspects of the definition and management of a CC service including costs/prices, catalog or SLA among others, together with the functionality such as a TS analysis.

In figure 4.3 a diagram can be seen combining both schemes to complete the description of a TS workflow with the management of a CC service.

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1.5 Validation

In addition to giving in the previous section of examples of TS modeling using tswf-schema, to reinforce the validity of the scheme as a mechanism for the definition of TS analysis services in CC, we have
carried out two additional validation actions, such as Marketplace of TS services for CC with tswf-schema and a set of competence questions (CQs).

5.1 TS Marketplace

Dealing with semantic definitions and descriptions, a test of the validity of the technology for practical purposes is to deploy these components effectively within service catalogs. These catalogs have a twofold function, on the one hand, to serve as a repository of service definitions and on the other hand to provide a point of service discovery by programmatic entities having the ability to understand the services exposed. An example of a service catalog with descriptions that can be imported, exchanged, discovered, and consumed has been designed as part of a TS Marketplace. The design of this Marketplace contains 3 key features:

- **Import**, where the platform allows users to include their own tswf-schema instances in json-ld or ttl format. With this tool, service descriptions are validated and included in the catalog. Once in the catalog, it is possible to use the composition tool where the workflow description can be modeled or viewed using the tswf-schema elements in a visual way. Figure 5.1 shows the workflow import diagram to the TS Marketplace and a part of the service catalog of available TS containing all the basic attributes and details deployed. For each TS it is possible to explore the definition and the components that integrate it, as well as the possibility to share/download each service available in the catalog.

- **Composition**, similar to other platforms, composition offers a complementary visual tool for creating/modifying TS workflows and services. In this sense it makes it much easier to compose workflows in general, since visually it is much more comfortable to use a visual tool than to code it manually. An example of the platform showing a workflow with example TS is shown in the Figure 5.1. In this figure a set of workflow operations that the service is capable of deploying are depicted.

- **Service consumption**, once the descriptions of tswf-schema instances are published, they are available for consumption either manually or automatically, for example, to deploy them from CC providers.

The platform is available for use in production in the website of the project [70] and the source code is available in a Github repository [71], in this way it is possible to deploy the TS Marketplace in any other provider of CC services.

5.2 Competency Questions (CQs)

Competency questions (CQs) [72] are used to specify the knowledge that has to be entailed in the ontology/vocabulary and thus can be considered to be requirements on the content of the ontology. A way to validate a semantic schema is the creation of a series of CQs to test whether the tswf-schema correctly fits the problem domain and is able to accurately solve the queries made to it. With these CQs we try to cover an important part of the definition of a TS service in CC, considering key elements such as, the study, analysis, or predictive models and also the management of the workflow of the TS itself within the CC provider (aspects like CC service management is shown in section 4.3).

The selected 10 CQs are the following:

- CQ01 How many operations [tasks] does the X TS workflow for predictive analysis have? Response: .
- CQ02 What services from the catalog [of a CC provider] enable the use of TS processing functions? Response: .
- CQ03 Does the TS service provide algorithms [functions] for predictive analysis using Deep Neural Networks and does it provide an SVM algorithm? Response: .
- CQ04 What data input does the TS workflow need with the X-identifier? Response: .
- CQ05 What are the outputs of the X-identifier of a TS workflow for the CC service? Response: .
- CQ06 What is the estimated economic cost of running a TS workflow analysis for the CC provider X? Response: .
- CQ07 Is there authentication for the execution of the TS service for provider X? Response: .
- CQ08 What is the parameterization of the ARIMA algorithm? Response: .
- CQ09 Can you display the prediction data for a horizon of X days for the Y workflow? Response: .
- CQ10 Which predictive model of the analysis produces the results with the lowest RMSE error? Response: .

The aim is to confirm that with tswf-schema is possible to capture partially the features of a specific TS service and it can be integrated into a service definition, through which make queries and manage this type of services for multiple CC providers. Dataset, CQs and SparQL queries (endpoint) are available on the project website [70].

6 Conclusions and future work

In this article we have introduced a scheme for the description of services in CC specifically designed for TS processing named tswf-schema. The scheme developed brings together all the commonly used operations in the study and analysis of TS, which allows transforming any implementation already developed in languages such as R or Python into a description based on semantic technology much richer, more homogeneous, and portable. This portability is key in terms of the fact that a single definition of a workflow with tswf-schema would be manageable and deployable in any CC service provider significantly facilitating the industrialization of services for CC environments.

With the scheme developed together with other complementary ones such as dmcc-schema, it is possible to include in the definition TS workflow all the elements related to the management of a CC service such as prices, SLA or instances, among other, taking advantage of the Linked Data proposal.

The selected use cases allow, on one hand, to show the user that any workflow implementation can be transformed into a semantic specification with tswf-schema ready to be consumed in CC environments, and on the other hand, it highlights the need to have a homogenization in the definition of this type of computing services, which unfortunately
the CC service providers market lacks. In addition, thanks to CQs it is possible to respond to a subset of desirable features that a service engineer in Cloud Computing might need. Both effectiveness and efficiency have been highlighted in the use case validation.

Finally, as a future work, we propose the implementation of a Cloud Computing services broker for TS that has the ability to optimize a workflow written in tsxfs-schema taking advantage of algorithm implementations and computing capabilities over different CC platforms.

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