# Semantically Enriching the Detrending Step of Time Series Analysis

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Abstract: In time series analysis, the trend extraction – detrending is considered a relevant step of preprocessing, where occurs the transformation of nonstationary time series in stationary, that is, free of trends. Trends are time series components that need be removed because they can hide other phenomena, causing distortions in further processing. To helping the decision making, by researchers, about how and how often the time series were detrended, the main contribution of this paper is semantically enriching this step, presenting the Detrend Ontology (DO prefix), designed in a modular way, by reuse of ontological resources, which are extended for modeling of statistical methods applied for detrending in the time domain. The ontology was evaluated by experts and ontologists and validated by means of a case study involving real-world photometric time series. It is described its extensibility for methods in time-frequency domain, as well as the association, when applicable, of instances with linked open data from DBpedia semantic knowledge base. As result of this paper, stands out the semantic enrichment of a relevant step of the analysis, contributing to the scientific knowledge generation in several areas that analyze time series.

## 1 INTRODUCTION

Time series (Chatfield, 2004) are observational data, obtained usually at regular intervals of time, in several knowledge areas. Time series can present four main components (Spiegel, 1985): seasonal, cyclic, irregular (noise or aleatory) and trends.

The trend component is the focus of this research, characterizing changes in the statistical measures of the nonstationary time series (which presenting trends), such as in the mean and/or variance/covariance, constituting long term movements. In the frequency domain, the trend is considered as a low-frequency component (Chandler and Scott, 2011).

Trends need be extracted from time series because they can hide other phenomena, as well as, if it does not occur the trend extraction step – detrending (Alexandrov et al, 2012), large distortions can occur in the further processing of probability density, correlation and spectral quantities, according to (Bendat and Piersol, 1986).

In an analysis process, usually, the time series analysis consists of two phases (Wu et al, 2007), preprocessing and analysis of data. In the preprocessing phase, occurs the trend extraction step, where several statistical methods can be applied for its correction.

The semantic knowledge, by researchers, about how and how often the stationary time series (free of trends) were detrended is relevant to decision making in an analysis process, as well as contributes to the choose of other statistical methods that can be applied for best results. However, the knowledge about the applicability of detrending methods is not always explicit and easy to interpret.

Time series can be semantically enriched using metadata - data about data. Nevertheless, these are free text and they can generate ambiguity in the generated data, as well as they can be insufficient to semantically enriching the detrending process.

Another way of generate semantic knowledge is by means of Ontology Web Language - OWL Ontologies in the Semantic Web context (Berners-Lee et al, 2001) which allowing semantically to enrich the time series, enabling logic inferences and interoperability, contributing to the understanding of the methods used and its applicability in the algorithms.

The main contribution of this paper is to present

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as the detrending step of time series analysis can be semantically enriched by means of the definition of an OWL domain ontology, developed from a modular design, considering the reuse and the extension of ontological resources, doing the association with the DBpedia knowledge base (DBpedia, 2015) and promoting semantic interoperability.

The Detrend Ontology (DO) defined is combined with the Time Series Provenance Ontology (de Souza et al, 2014b) and with a provenance model for generating information about time series provenance, detrending methods and which agent and processes were applied in time series (de Souza et al, 2014a), contributing to improve the decision making about a relevant step of time series analysis (de Souza et al, 2014c).

Beyond this introduction, this paper presenting more four sections. The second section describes the theoretical foundation. The third section reports the methodology and presents the main contribution of this paper, describing the evaluation and validation in a real-world case study and its extensibility. In the fourth section are described and compared the related works. Finally, are presented the conclusions and future researches.

## 2 THEORETICAL FOUNDATION

Ontologies (Guarino, 1998) allow representing the knowledge in a structured way, enabling logic inferences by means of reasoners as Pellet; creation of rules in Semantic Web Rule Language - SWRL Language; and the development of queries in SPARQL Protocol and Resource Description Framework Query Language - SPARQL Language. OWL is the language used for development of ontologies in the Web, being used the OWL-DL version, based on Descriptive Logic (DL).

An ontology is formed by classes, instances and relationships. A class is a set of individuals or instances, sharing commons characteristics. A relationship allows the association between classes.

The association, when applicable, of instances with the DBpedia knowledge base (DBpedia, 2015) allows semantic interoperability and the generation of more knowledge from the linked open data in the Semantic Web.

Several detrending software using different statistical methods can be used for trend extraction. The time series analysis can be done using methods in its usual domain, that is, in the time domain or, in the frequency domain, where the trend component is analysed on the all signal and information about time domain are lost. Also the analysis can be in the time-frequency domain, considering both domains (Meinl, 2011).

One of possibilities for trend extraction is to use statistical methods that allow its estimation, which is extracted from time series. Among the methods that can be used with this objective in time domain, stand out the parametric methods, such as linear, nonlinear or multiple regression analysis (Hair et al, 2010), or nonparametric methods, such as nonparametric regression, based on some form of time series smoothing (Shumway and Stoffer, 2006). Other methods used for its extraction include the use of digital filters (Chandler and Scott, 2011).

## 3 DETREND ONTOLOGY

The Ontology Development 101 (Noy and McGuinness, 2001) and Neon Methodology (SuarézFigueroa et al, 2012) were used complementarily for the development of the domain ontology. The Neon Methodology allows the choice of nine alternatives scenarios, including specific scenarios to describe the reuse of ontologies and semantic declaration, presenting detailed steps for the development of the ontologies, as well as allows the use of a modular design. For development of the DO Ontology, besides of the Scenario 1, also were used the Scenario 3 for reuse of ontological resources and the Scenario 8 for its restructuring.

For its development, was considered the reuse of semantic declarations from Semantic Web for Earth and Environmental Terminology - SWEET Ontology (SWEET, 2015) and the StatisticalAnalysis Ontology (Statistical Analysis, 2015) was used and extended for modeling of other detrending methods.

According to Neon Methodology, it was elaborated the Ontology Requirements Specification Document – ORSD, describing the ontology proposal, scope, implementation language, users and requisites. The competence questions were divided in groups, including questions related with parametric and non-parametric methods.

About the reuse of ontological resources, to modeling of software and parameters, the following ontologies were analysed: i. The Software Ontology (SWO Ontology, 2014); ii. Core Software Ontology (CSO Ontology, 2014); Core Ontology of Programs and Software (Lando et al, 2009); EvoOnt - A Software Evolution Ontology (EvoOnt, 2014 and SEON - Software Evolution ONtologies (Seon, 2014). For other modeling, the following ontologies also were analysed: i. ACM Ontologies (ACM Ontologies, 2014); Semantic Web for Earth and Environmental Terminology (SWEET, 2015); Ontology Computer Science for Non-Computer Scientists (CSnCS Ontology, 2014); reprMathStatistics Ontology (reprMathStatistics Ontology, 2014) and Sciflow: A Scientific Workflow Ontology (Sciflow, 2014). By observed reasons, the above ontologies were not considered for reuse and extension, including the analysis of experts.

The ontology called StatisticalAnalysis.owl (Statistical Analysis Ontology, 2015) is imported, which is extended for modeling of statistical methods and its applicability in detrending algorithms.

For the extension of the ontology, it was done a search in glossaries, vocabularies, nomenclatures and norms. About the definition of the concepts, the same were described from bibliography of the area. The following references also were analysed: i. Glossary Of Statistical Terms (OECD Glossary, 2014); ii. Terminology on Statistical Metadata (TerminologyonStatisticalMetadata, 2014); iii. International Statistical Institute (ISI, 2014); Statistics Glossary (STATS, 2014); Statistical Techniques in the Data Library: A Tutorial (StatTutorial, 2014); ISO Norms (3534-1:2006, 3534-2:2006 e 3534-3:1999) (ISO Norms, 2014); Norma Brasileira ABNT NBR ISO 3534-1. 1a. Ed. 2006 - 2010 (Norma Brasileira, 2014); DCMI Type Vocabulary (DCMI, 2014), from this was created and defined the (dcmitype:Software) class, which is extended using the ACM Taxonomy (ACM Taxonomy, 2014) to modeling of the programming languages.

Some facts were analysed and considered in the modeling of the DO Ontology. In the preprocessing phase of time series analysis, the researcher can observe the time series components in an isolated way, applying specific methods for correction of certain component. In the case of the time series present the irregular component in an excessive way, can be necessary the use of a filter method for its correction, process called denoising.

The DO Ontology considers also this scenario, where the time series can be corrected from the noise. Thus, were modeled the algorithms and software that can be used for this purpose.

In preprocessing phase, a same method can be used for more once task (Alexandrov et al, 2012). For example, the Singular Spectrum Analysis – SSA method (Vautard and Ghil, 1989) can be used to trend extraction, denoising, prevision and change-point detection. Likewise, other filter methods can be used, both to detrending and to denoising (Flandrin et al, 2004). According to Meinl (2011), the smoothing methods and denoising sometimes are used as synonymous. However, the smoothing denotes the removal of irregulars detail (shark's fins), producing a smooth version of raw time series. Denoising aims the noise removal (short term changes with low amplitude), from time series that does not necessarily results in a smooth signal, according to Meinl (2011).

Aiming to model this scenario, are described algorithms and software of detrending and denoising. The filtering algorithms remove the noise of time series and the detrending algorithms are related with the estimation and/or removal of trends from time series. The Classes Diagram (Figure 1) shows the main classes of the DO Ontology.

From reuse of (math:NumericalEntity), subclasses (solu:Solution) and (solu:Algorithm), are created the classes (do:PreprocessingAlgorithm) and subclasses of filtering and detrending algorithm. From reuse of (dcmitype:Software) class, it is created the subclass (do:PreprocessingSoftware) and its subclasses of detrending and filtering software. These algorithms/software can be a version of other algorithms/software, modeled according to an auto-relationship in the respective class.

In DO Ontology, it is considered that a same method can be used to realize more once task in the time series, thus are created the classes (do:TimeSeriesCorrectionMethod), describing the methods and the (do:AlgorithmMethodApplicability), to describe the applicability of the method in certain algorithm. To exemplify, the (do:Moving Average) class related with the moving average method, it can be used in an algorithm to denoising task, constituting, in frequency language, a filter that allows to pass the low-frequency component as the trend, removing the high-component that is the noise. This method also can be used in an algorithm to nonparamentric trend estimation, where the fluctuations are considered belonging to trend, according to (Chandler and Scott, 2011).

This choice depends on context, considered in ontology modeling, being possible to declare the method and which is its applicability in the respective algorithm. The objective of this modeling it is to facilitate the understanding about the method used and what was done in the time series with its application. The (do:Domain) class is related with the domain of the methods, where the instances are associated with the DBpedia as means of semantic

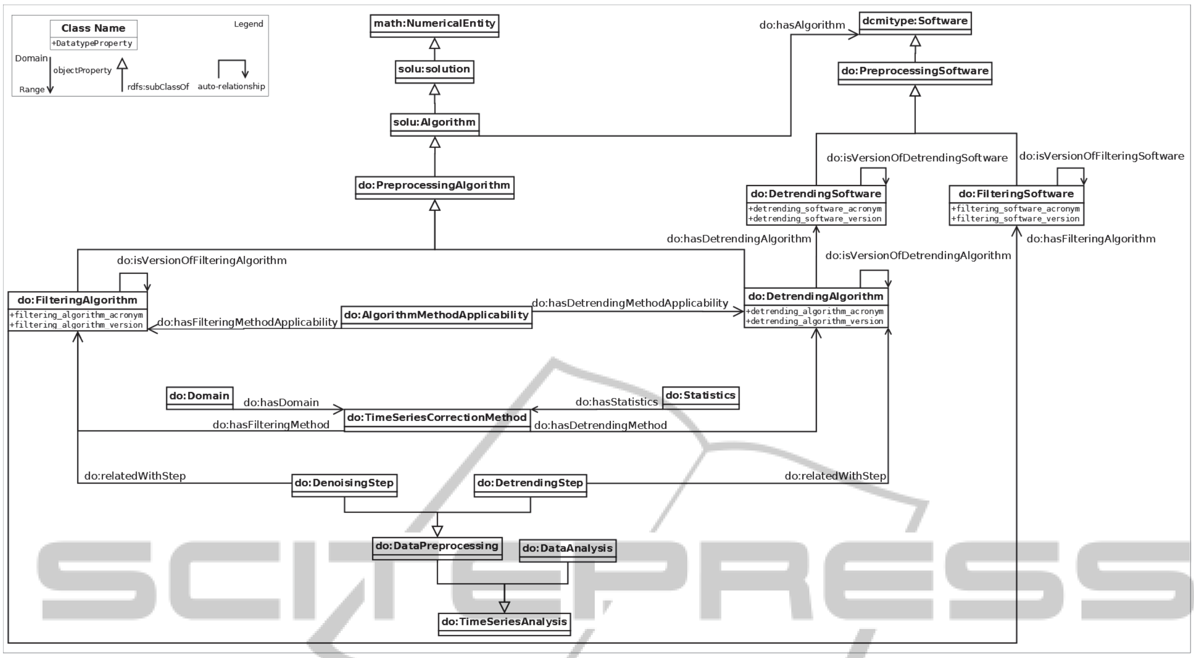




Figure 1: DO Ontology Classes Diagram.

interoperability. The (do:Statistics) class describes the Statistics of the methods, Parametric, Semi-Parametric or Non-Parametric.

The detrending or filtering algorithm classes are associated with the respective step by means of the (do:relatedWithStep) relationship. The (do:DetrendingStep) and (do:DenoisingStep) classes are declared as subclass of (do:DataPreprocessing), disjoint of (do:DataAnalysis), both subclasses of (do:TimeSeriesAnalysis) class.

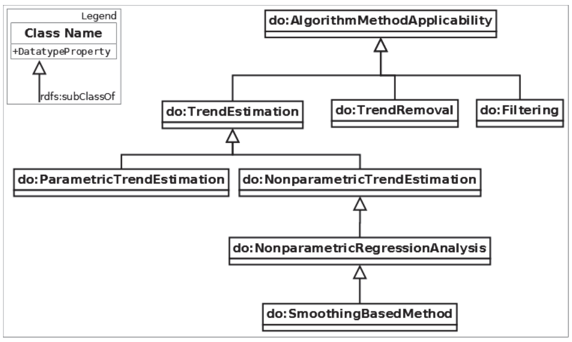


Figure 2: Class (do:AlgorithmMethodApplicability).

The Figure 2 presents the applicability of the methods in the algorithms: trend estimation, trend removal and filtering. A determined method can be used for parametrically trend estimation, using a regression regression analysis method or, nonparametrically, using nonparametric regression, based on some smoothing method (Chandler and Scott, 2011). The method applicability also can be related with the trend removal, using a filter that allows to pass the high-frequency component that is the noise component and removing the trend component that is of low-frequency. Also it can be related with the use of some filter method for noise removal. The Figure 3 presents above an example of a query in SPARQL Language and bellow the answer from knowledge base related with detrending algorithms, methods and its applicability.

The DO Ontology was evaluated according to the Functional Evaluation (SuarézFigueroa et al, 2012)**,** in its use context, by experts and ontologists. The feedback from evaluators was considered essential, due to applicability of the ontology.

As means of validation of the DO Ontology, after the combination in the Detrend Provenance Model - dpm prefix (de Souza et al, 2014a), the ontology was validated with real-world photometric time series in a case study involving two use cases which can be seen in Figure 3, among other. The first use case is related with the Corot Detrend Algorithm (Mislis et al, 2010) using the regression analysis method, applied to cubic trend estimation and using cubic regression analysis. In the second use case is applied the Corot Detrend Algorithm Modified (Boufleur, 2012) using the robust moving average method, a low-pass filter that remove the high-frequency component, smoothing the trend component of low-frequency, applied to moving average filter based smoothing and using the moving

- Query in SPARQL:

```
SELECT distinct ?detrendingalgorithm ?detrendingmethod ?detrendingmethodapplicability ?filter ?analysis
WHERE {{ ?detrendingalgorithm do:hasDetrendingMethod ?detrendingmethod ;
                              do:hasDetrendingMethodApplicability ?detrendingmethodapplicability .
                              ?detrendingmethodapplicability do:hasFilter ?filter .}
UNION { ?detrendingalgorithm do:hasDetrendingMethod ?detrendingmethod ;
                             do:hasDetrendingMethodApplicability ?detrendingmethodapplicability .
                             ?detrendingmethodapplicability do:hasAnalysis ?analysis .}
```

| detrendingalgorithm | detrendingmethod | detrendingmethodapplicability | filter | analysis |
|---|---|---|---|---|
| Corot_Detrend_Algorithm_Modified | Robust_Moving_Average | Moving_Average_Filter_Based_Smoothing | Moving_Average_Filter | |
| Differencing_Detrending_Algorithm | Differencing | First_Differencing_Filter_Based_Detrending | First_Differencing_Filter | |
| High_Pass_Gaussian_Filter_Based_Detrending_Algorithm | Gaussian | High_Pass_Gaussian_Filter_Based_Detrending | Gaussian_High_Pass_Filter | |
| Corot_Detrend_Algorithm | Regression_Analysis | Cubic_Trend_Estimation | | Cubic_Regression |
| Spline_Regression_Based_Detrending_Algorithm | Spline | Spline_Regression_Based_Smoothing | | Cubic_Spline_Regression |
| Nearest_Neighbor_Based_Detrending_Algorithm | Nearest_Neighbor | Nearest_Neighbor_Regression_Based_Smoothing | | Nearest_Neighbor_Linear_Regression |
| Linear_Regression_Simple_Based_Detrending_Algorithm | Regression_Analysis | Linear_Trend_Estimation | | Ordinary_Least_Square_Linear_Regression |
| Loess_Detrending_Algorithm | Loess | Loess_Smoothing | | Loess_Regression |

Figure 3: Query about methods and its applicability in the detrending algorithms.

average filter. The estimated or smoothed trend is removed by subtraction operation from raw time series.

About the extensibility of DO Ontology, are modeled the following methods of the time-frequency domain: Singular Spectrum Analysis - SSA (Vautard and Ghil, 1989), Empirical Mode Decomposition - EMD (Huang, 1998) and Ensemble Empirical Mode Decomposition - EEMD (Wu and Huang, 2009), from (do:Filtering) class. These methods are data adaptive filter by nonlinear way, which can be used for trend extraction or noise removal.

# 4 RELATED WORKS

The related works with this research are: (Henson et al, 2009), (Bozic, 2011), (Bozic and Winiwarter, 2012), (Bozic and Winiwarter, 2013), (Bozic et al, 2014), (Compton et al, 2012), (Llaves and Renschler, 2012), (Sheth et al, 2008), which were compared according to criteria considered relevant for the development of the ontology, stand out the following questions (de Souza et al, 2014c):

- Time series observations can be described using the OWL Language, where domain ontologies are used to semantically enriching the time series.
- A design pattern used to describe time series observations is the Observations and Measurements (O&M Model), proposed by Open Geospatial Consortium/Sensor Web Enablement, which presenting syntactic interoperability, but it need be adapted for OWL Language to allow semantic interoperability.
- It is possible to associate the necessities of users with the data (time series), contributing for decision making by researchers.
- In the environmental time series, can occur different interpretation of fundamental concepts, such as Sensor. In this cases, it is usually chosen the broader definition to that the same be specialized in sub-concepts.
- The Simple Knowledge Organization System Reference Vocabulary (SKOS Vocabulary) can be used for definition of terms, as in Semantic Sensor Network - SSN Ontology (Compton et al, 2012).
- Terms can be associated with Linked Sensor Data and Linked Open Data, as means of promoting semantic interoperability.
- SWEET Ontologies are reused as a pattern to represent environmental and earth sciences.
- The modular development can be considered as the case of SSN Ontology, conceptually organized in ten modules, which can be mapped to a physical modularization.
- When is done a mapping to a Foundation Ontology, the ontology considered is the Dolce Ultralite – DUL (Dul Ontology, 2014), due to its lightness, considering other Foundation Ontologies.
- Ontology Design Patterns (ODPs) are considered in the domain ontologies design.
- Also interoperability questions may occur from different communities, using the same term to refer to various occurrences, where this problem must be treated semantically.

Based on related works, the characteristics considered relevant and appropriate in the development of the ontologies were identified and considered in the DO Ontology definition, such as: i. modular development; ii. definition of concepts and of properties using the tags (rdfs:comment) and (rdfs:label); iii. association of the instances with the DBpedia; iv. reuse of semantic declaration from SWEET Ontology; and v. reuse and extension of the StatisticalAnalysis Ontology.

So, stand out among the related works analysed, that no studies were found evidencing the semantic enriching by means of OWL ontologies, developed in a modular design and considering reuse and the association with the linked open data of detrending methods in the time domain, extensible to the frequency domain, contributing to improving the decision making in an analysis process.

# 5 CONCLUSIONS AND FUTURE RESEARCHES

Nowadays, time series are obtained in several areas, which need be analysed for generating scientific knowledge. The focus of this work is the trend component, constituting changes in the statistical measures of the time series, characterized as a long term movement.

The nonstationary time series need be corrected because the most of statistical methods are developed for stationarity, also trends can hide other phenomena, presenting distortions in further processing. So far, there is not a detrending method considered as universal in all application areas. So, several detrending methods can be applied to detrending the time series.

Given the need to add semantic knowledge in the detrending step of time series analysis as means of contributing to improve an important step of preprocessing, the main contribution of this paper is presenting a domain ontology, developed in OWL Language, entitled Detrend Ontology. Its design is modular, considering the reuse and extension of ontological resources and association with linked open data to semantic interoperability. All classes are defined using nomenclature from time series analysis. The ontology was evaluated by experts of the area and by ontologists, where the feedback from evaluators was considered essential.

The ontology was validated in a case study where real-world photometric time series were detrended. Also it is described its extensibility for modeling of methods in time-frequency domain. It contributes for the understanding about how and how often the time series were detrended, allowing to the researcher to choose other statistical methods that can be applied for best results. As result, stands out the semantic enrichment of a relevant step of the analysis, contributing with the scientific knowledge generation in many areas that analyze time series.

How futures researches stands out the extension of modeling of the methods in the frequency domain, such as Wavelet methods, among other. Another suggestion is the reuse of the Semantic Web for Research Communities Ontology (SWRC Ontology, 2015) for modeling of detrending publications.

# REFERENCES


ACM Ontologies. URL:http://acm.rkbexplorer.com/, Aug. 2014.

ACM Taxonomy. URL:http://dl.acm.org/. Nov. 2014.

Alexandrov, T. et al., 2012. A Review of Some Modern Approaches to the Problem of Trend Extraction. *Econometric Reviews*. Vol. 31, Number 6, pages 593-624.

Bendat, J. S., and Piersol, A. G., 1986. *Random Data: Analysis and Measurement Procedures*, 2nd ed. John Wiley and Sons, Inc., New York, USA.

Berners-Lee, T., Hendler, J., and Lassila, O., 2001. The semantic web. *Scientific American* 284, 5. 34–43.

Boufleur, R. C., 2012. A busca de exoplanetas com as curvas de luz do corot. Dissertação de mestrado, Curso de Pós-Graduação em Astronomia, R.J., Brasil.

Bozic, B., 2011. Simulation and modeling of semantically enriched time series. *19th International Congress on Modelling and Simulation*, 12–16.

Bozic, B., and Winiwarter, W., 2012. Community building based on semantic time series. *iiWAS*, 213–222.

Bozic, B., and Winiwarter, W., 2013. A showcase of semantic time series processing. *IJWIS* 9, 2 117–141.

Bozic, B., Peters-Andersa, J., and Schimaka, G., 2014. Ontology mapping in semantic time series processing and climate change prediction. *International Environmental Modelling and Software Society (iEMSs).*

Chandler, R., and Scott, M., 2011. *Statistical Methods for Trend Detection and Analysis in the Environmental Sciences*, 1nd ed. Wiley.

Chatfield, C., 2004. *The Analysis of Time Series: An Introduction*, 6th ed. *CRC Press*, Florida, US.

Compton, M. et al, 2012. The ssn ontology of the w3c semantic sensor network incubator group. *Web Semantics: Science, Services and Agents on the WWW* 17, 0.

CSO Ontology. Core Software Ontology. URL:http://cos.ontoware.org/cso, July 2014.

CSnCS Ontology. URL:http://watson.kmi.open.ac.uk/ontologies/LT4eL/CSnCSv0.01Lex.owl, June 2014.

DBpedia. URL: http://dbpedia.org/, Jan 2015.

DCMI Type Vocabulary. URL:http://dublincore.org/documents/2000/07/11/dcmi-type-vocabulary/, Oct. 2014.

de Souza, L., VAZ, M. S. M. G., SUNYE, M. S., 2014a. Modular development of ontologies for provenance in detrending time series. In: *Eleventh Int. Conf. on Inf. Tech: New Generations (ITNG)*. Las Vegas, p. 567-572.

de Souza, L., VAZ, M. S. M. G., SUNYE, M. S., 2014b. Domain Ontology for Time Series Provenance. In: *16th International Conference on Enterprise Information Systems*. *ICEIS*. Lisbon, p. 217-224.

de Souza, L., 2014c. Um modelo de proveniência para extração de tendências em séries temporais. Tese de Doutorado. Or. Sunye, M. S. e Vaz, M. S. M. G. Programa de Pós-Graduação em Informática. UFPR, Brazil. 256 pp.
Dul Ontology. URL:http://www.loa-cnr.it/ontologies/DUL.owl, Feb. 2014.
EvoOnt Ontology. URL:https://files.ifi.uzh.ch/ddis/oldweb/ddis/research/evoont/, June 2014.
Flandrin, P., Gonçalves, P., and Rilling, G., 2004. Detrending and denoising with empirical mode decompositions. *In EUSIPCO-04 (2004)*, pp. 1581–1584.
Guarino, N., 1998. Formal ontology and information systems. In *Proceedings of FOIS'98*, Trento, Italy, 6-8. Amsterdam, N. Guarino, Ed., IOS Press, pp. 3–15.
Hair, J. F. Jr., Black, W.C., Babin, B.J., Anderson, R. E., 2010. *Multivariate Data Analysis*. 7th edition. Pearson Prentice Hall.
Henson, C. A., H. Neuhaus, H., Sheth, A. P., Thirunarayan, K., and Buyya, R., 2009. An ontological representation of time series observations on the semantic sensor web. *Proc, of 1st Intern. Workshop on the Semantic Sensor Web*. Herkalion, Greece.
Huang, N. E., and et al., 1998. The empirical mode decomposition and the Hubert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society A* 454, 1971.
ISI. International Statistical Institute. URL:http://isi.cbs.nl/glossary/bloken00.htm, Sept. 2014.
ISO Norms (3534-1:2006, 3534-2:2006 e 3534-3:1999). URL:http://www.iso.org/iso/home/, Oct. 2014.
Lando, P., Lapujade, A., Kassel, G., and Furst, F., 2009. An ontological investigation in the field of computer programs. *In Software and Data Tech., Communications in Computer and Inf. Science.* 22, 371–383.
Llaves, A., and Renschler, C. S., 2012. Observing changes in real-time sensor observations. *In Multidisciplinary Research on Geographical Information in Europe and Beyond.*
Meinl, T., 2011. A Novel Wavelet Based Approach for Time Series Data Analysis. PhD thesis, Karlsruhe.
Mislis, D., Schmitt, J. H. M. M., Carone, L., Guenther, E. W. and Patzold, M., 2010. An algorithm for correcting corot raw light curves. *arXiv/1008.0300*.
Norma brasileira abnt nbr iso 3534-1. 1a. ed. 2006 - 2010. URL:http://www.abntcatalogo.com.br/, Oct. 2014.
Noy, N. F., and McGuinness, D. L., 2001. Ontology development 101: A guide to creating your first ontology. *Development 32*, 1 (2001), 1–25.
OECD Glossary. URL:http://stats.oecd.org/glossary/index.htm, Aug. 2014.
ReprMathStatistics Ontology. URL:http://sweet.jpl.nasa.gov.gov/2.3/reprMathStatistics.owl, Sept. 2014.
Sciflow a scientific workflow ontology. URL:http://www.lbd.dcc.ufmg.br/colecoes/sbbd/2011/0016.pdf, Oct. 2014.
Seon Ontologies. URL:http://www.se-on.org/, July 2014.
Sheth, A., Henson, C., and Sahoo, S. S., 2008. *Semantic sensor web. IEEE Internet Computing* 12, 4. 78–83.
Shumway, R.H., and Stoffer, D. S. 2006. *Time series analysis and its applications: with R examples*. 2nd ed. Springer.
Spiegel, M. R., 1985. *Estatística*. McGraw-Hill, São Paulo, Brazil.
Statistical Analysis Ontology. URL: URL:http://a.com/StatisticalAnalysis.owl. Dec, 2015.
StatTutorial. Statistical techniques in the data library: A tutorial. URL:http://iridl.ldeo.columbia.edu/dochelp/Stat.
Tutorial/, Sept. 2014.
STATS. Statistics glossary. URL:http://www.stats.gla.ac.uk/steps/glossary/paired_data.html, Oct. 2014.
SuarézFigueroa, M. C., Gomez-Perez, A., Motta, E., and Gangemi, 2012. *A. Ontology Engineering in a Networked World*. Springer-Verlag Berlin Heidelberg.
SWEET Ontology. URL: http://sweet.jpl.nasa.gov/2.3/sweetAll.owl, Dec, 2015.
SWO Ontology. The Software Ontology. URL:http://purl.bioontology.org/ontology/SWO, June 2014.
SWRC Ontology. Semantic Web for Research Communities Ontology. URL:http://ontoware.org/swrc/, Jan, 2015.
Terminology on statistical metadata. URL:http://www.unece.org/fileadmin/DAM/stats/publications/53metadaterminology.pdf, July 2014.
Vautard, R. P. Y., and Ghil, M., 1989. Singular spectrum analysis in nonlinear dynamics with applications to paleoclimatic time series. *Physica D* 35, 395–424.
Wu, Z., and Huang, N. E., 2009. Ensemble empirical mode decomposition: a noise-assisted data analysis method. *Advances in Adaptive Data Analysis* 1, 1, 1–41.
Wu, Z., Huang, N. E., Long, S. R., and Peng, C., 2007. On the trend, detrending, and variability of nonlinear and nonstationary time series. *Proc. Nat. Academy of Sciences 104*, 38, 14889–14894.