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Advances on Data Management and Information Systems

Jérôme Darmont[1] · Boris Novikov[2] · Robert Wrembel[3] · Ladjel Bellatreche[4]

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1 Introduction

The research and technological area of data management encompasses various concepts, techniques, algorithms and technologies, including data modeling, data integration and ingestion, transactional data management, query languages, query optimization, physical data storage, data structures, analytical techniques (including On-Line Analytical Processing – OLAP), as well as service creation and orchestration (Garcia-Molina et al., 2009). Data management technologies are core components of every information system, either centralized or distributed, deployed in an on-premise hardware architecture or in a cloud ecosystem. Data management technologies have been used in commercial, mature products for decades. They were originally developed for managing structured data (mainly expressed in the relational data model).

Yet, the ubiquitous big data (Azzini et al., 2021) require development of new data management techniques, suitable for the variety of data formats (from structured, through semi-structured, to unstructured), overwhelming data volumes and velocity of big data generation. These new techniques draw upon the concepts applied to managing relational data.

One of the most frequently used data format for big data is based on graphs, which are a natural way of representing relationships between entities, e.g., knowledge, social connections and components of a complex system. Such data not only need to be efficiently stored but also efficiently analyzed. Therefore, some OLAP-like analysis approaches from graph data have been recently proposed, e.g., Chen et al. (2020), Ghrab et al. (2018), Ghrab et al. (2021), and Schuetz et al. (2021). Thus, combining graph and OLAP technologies offers ways of analyzing graphs in a manner already well accepted by the industry (Richardson et al., 2021).

The complexity of ecosystems for managing big data results in challenges for orchestrating these components and in optimizing their performance, as there are too many parameters in each system to be manually tuned by a human administrator. Thus, more and more frequently, machine learning techniques are applied to performance optimization, e.g., Hernández et al. (2018) and Witt et al. (2019). Conversely, data management techniques are used to solve challenges in machine learning, such as building end-to-end data processing pipelines (Romero & Wrembel, 2020).

In this editorial to the special section of Information Systems Frontiers, we outline research problems in graph processing, OLAP and machine learning. These problems are addressed by the papers in this special section.

2 Selected Research Problems in Data Management and Information Systems

2.1 Graph Processing

Graph processing algorithms have been attracting attention of researchers since the 1950's. Several knowledge representation techniques (such as semantic networks) studied in the 1970's utilize graph structures, including applications to rule-based systems (Griffith, 1982), data structures for efficient processing (Moldovan, 1984)), and several other aspects.

✉ Robert Wrembel
robert.wrembel@cs.put.poznan.pl

Jérôme Darmont
jerome.darmont@univ-lyon2.fr

Boris Novikov
borisnov@acm.org

Ladjel Bellatreche
ladjel.bellatreche@ensma.fr

[1] Universié Lumière Lyon 2, Lyon, France

[2] HSE Unviersity, Saint Petersburg, Russia

[3] Poznan University of Technology, Poznan, Poland

[4] École Nationale Supérieure de Mécanique et d'Aérotechnique, Poitiers, France

The concepts of semantic networks served as a base for the Semantic Web and evolved into knowledge graphs, also known as knowledge bases. Processing of large distributed RDF knowledge bases with the SPARQL language is addressed in Peng et al. (2016).

Graph-based models become a natural choice for a representation of semi-structured data (McHugh et al., 1997). Graph representations proved their usefulness for modeling hypertexts, including the World Wide Web (Meusel et al., 2014). Documents (e.g., Web pages) are mapped to vertices, while directed edges represent links. The graph representations of the WWW provided several features (such as page rank and simrank) for deep analysis of its structure and definition. Sources of large graphs include social networks, bioinformatics, road networks, and other application domains.

The need to store and process large graphs supports growing interest to graph databases. An overview of several aspects of graph databases can be found in (Deutsch & Papakonstantinou, 2018). Typically, such databases can store graph vertices and nodes, labeled with sets of attributes. A widespread opinion states that graph databases provide more powerful modeling features than the relational model used in traditional relational databases. This is doubtful, as a relational database schema (represented for example as an ER model) is also a graph (Pokorný, 2016). Actually, the advantage of graph databases is that the expensive and time-consuming modeling can be pushed forward to later phases of the information system lifecycle, providing more options for rapid prototyping and similar application development methodologies (Brdjanin et al., 2018).

A need of highly expressive tools for graph processing specification triggered a number of efforts in declarative query languages design. A step toward the standardization of graph query languages (Angles et al., 2018) is focused on providing a balance between high expressiveness and computational performance, avoiding constructs that may result in unacceptable computation complexity. The GSQL graph query language (Deutsch et al., 2020) supports the specification of complex analytical queries over graphs, including pattern matching and aggregations. A comparison of different graph processing techniques, available in the Neo4j graph database management system, can be found in Holzschuher and Peinl (2013).

Several similarities can be found between relational and graph declarative query languages: as soon as sets of labeled nodes or edges are produced as intermediate results, the remaining processing is typically expressed in terms of relational operations. The most significant differences between graph and relational database query languages follow.

- Graph traversal (implicit and rarely used in relational languages) requires the intensive use of recursion and an efficient implementation in graph databases.
- Graph query languages provide support for computationally complex processing, such as weighted shortest path search, potentially with additional constraints.
- Locality of data placement is essential for high performance of relational systems. Data placement in graph databases is much more complex and often results in poor performance when the size of the database exceeds the available main memory of a single server.

The items listed above are inter-related: the performance of graph processing depends on locality needed for efficient traversing of a graph. However, traversing depends on the problem being solved. A generic approach is to rely on certain graph properties to optimize the storage of graph nodes and edges, that is, graph partitioning.

2.2 On-Line Analytical Processing

The term “On-Line Analytical Processing” (OLAP) was coined by Edgar F. Codd in 1993 (Codd et al., 1993). OLAP is defined in contrast to *operational* database systems that run On-Line Transactional Processing (OLTP). In OLTP, data representing the current state of information may be frequently modified and are interrogated through relatively simple queries. OLAP’s data are typically sourced from one or several OLTP databases, consolidated and historicized for *decision-support* purposes. They are seldom modified and are queried by complex, analytical queries that run over large data volumes.

Conceptually, OLAP rests on a metaphor that is easy to grasp by business users: the (hyper)cube. Facts constituted of numerical Key Performance Indicators (KPIs), e.g., product sales, are analysis subjects. They are viewed as points in a multidimensional space whose dimensions are analysis axes, e.g., time, store, salesperson, etc. Dimensions may also have hierarchies, e.g., $store \rightarrow city \rightarrow state$. Thus, dimensions represent the coordinates of facts in the multidimensional space.

In the 1990’s, OLAP research mainly focused on designing efficient logical and physical models, synthetically surveyed by Vassiliadis and Sellis (1999). Relational OLAP (ROLAP) relies on storing data in time-tested relational Database Management Systems (DBMSs), complemented with new, OLAP-specific operators and queries available in SQL99. ROLAP is cheap and easy to implement, can handle large data volumes, and schema evolution is relatively easy. However, ROLAP induces numerous, costly joints that hinder query performance, and analysis results are not suitable to end-users, i.e., business users, and thus must be reformatted.

In contrast, Multidimensional OLAP (MOLAP) sticks to the cube metaphor. Hypercubes are natively stored in multidimensional tables, allowing quick aggregate computations. However, it turned out that MOLAP systems and languages (e.g., MDX) were in majority proprietary and difficult to implement. Moreover, data volume is limited to the RAM size and a cube can be quite sparse, wasting memory. Eventually, refreshing the system is limited, inducing full and costly periodical reconstructions.

Eventually, Hybrid OLAP (HOLAP) was proposed as the best of both worlds (Salka, 1998), by storing atomic data in a relational DBMS and aggregated data in MOLAP cubes, thus achieving a good cost/performance tradeoff on large data volumes. However, HOLAP is difficult to implement and neither as fast as MOLAP nor as scalable as ROLAP. Later on, in 2014, Gartner introduced the Hybrid Transaction/Analytical Processing (HTAP[1]), where an in-memory DBMS helps process OLTP and OLAP simultaneously, which allows transactional data to be quickly available for analytics and induces fast, distributed query computation while avoiding data redundancy. However, this is a complex and drastic change in decision-support architectures.

After OLAP pioneers, many lines of research went on for more than fifteen years, which can be classified in two trends. In the first trend, OLAP is adapted to particular data formats. One of the most prominent of such adaptations is probably Spatial OLAP (SOLAP Han, 2017), where OLAP is applied on spatial (and even spatio-temporal) data, allowing for example to zoom and dezoom (i.e., drill-down and roll-up in terms of OLAP operations) spatial representations such as maps. Another well-researched adaptation was XML-OLAP (also called XOLAP), which allows OLAP on semi-structured data. Related approaches are surveyed in Mahboubi et al. (2009). Other examples include OLAP on trajectory data (Marketos & Theodoridis, 2010) and mobile OLAP (Maniatis, 2004).

In the second trend, OLAP is hybridized with other techniques for specific purposes. Quite quickly, OLAP was associated with data mining, with OLAP providing data navigation and identifying a subset of a cube; and data mining featuring association, classification, prediction, clustering, and sequencing on this data subset (Han, 1997).

With the Web becoming an important source of data, OLAP systems could not rely only on internal data any more and had to discover external, Web data, as well as their semantics. This issue was addressed with the help of Semantic Web (SW) technologies that support inference and reasoning on data. An extensive survey covers this research trend (Abelló et al., 2015). OLAP was also combined with information networks akin to social media, in the sense that they can be represented by very similar graphs. A comprehensive survey of the so-called Graph OLAP, with a focus on bibliographic data analysis, is provided in Loudcher et al. (2015).

Eventually, the Big Data era made OLAP meet new challenges such as: (1) design methods that handle a high complexity that tends to make the number of dimensions explosive; (2) computing methodologies that leverage the cloud computing paradigm for scaling and performance; and (3) query languages that can manage data variety (Cuzzocrea, 2015).

Big Data also pushed forward the exploitation of textual documents, which are acknowledged to represent the majority of the information stored worldwide. In the context of OLAP, i.e., Text or Textual OLAP, the key issue is to find ways of aggregating textual documents instead of numerical KPIs. Two trends emerge, based on the hypercube structure and text mining, respectively. They are thoroughly surveyed and discussed in Bouakkaz et al. (2017).

Finally, with the emergence of Data Lakes (DLs) in the 2010's, the concept of Data Warehouse (DW), on which OLAP typically rests, is challenged in terms of data integration complexity, data siloing, data variety management and even scaling. However, DLs and DWs are actually synergistic. A DL can indeed be the source of a DW, and DWs can be components, among others, of DLs. Thence, OLAP remains very useful as an analytical tool in both cases. Two recent and complimentary surveys cover DL, DW and OLAP-related issues (Sawadogo & Darmont, 2021; Hai et al., 2021).

2.3 Machine Learning

Artificial intelligence (AI) has been a hot research and technological topic for a few years. AI refers to the computing techniques that allow stimulation of human-like intelligence in machines. AI is a broad area of research and technology that includes a sub-area - Machine Learning (ML), which enables a computer system to learn models from data.

[1] https://www.gartner.com/imagesrv/media-products/pdf/Kx/KX-1-3CZ44RH.pdf

The most frequent ML techniques include regression, clustering, and classification (they are supported by multiple software tools (Krensky & Idoine, 2021)). Regression aims at building statistical models to predict continuous values (e.g., electrical or thermal energy usage in a given point in time or time period). Clustering aims at dividing data items into a non-predefined number of groups, such that the instances in the same group have similar values of some features (e.g., grouping customers by their purchase behaviour). Classification aims at predicting a predefined class to which belongs a given data item (e.g., classifying patients into a class of high blood pressure risk or a class of no-risk).

ML in turn includes a sub-area - Artificial Neural Networks (ANNs). ANNs are based on a statistical model that reflects the way a human brain is build, thus it mathematically models how the brain works. ANNs are the foundation of Deep Learning (DL) (Bengio et al., 2021). DL applies algorithms that allow a machine to train itself from large volumes of data, in order to learn new models based on new input (data). DL turned out to be especially efficient in image and speech recognition.

In order to build prediction models by ML algorithms, massive amounts of pre-processed data are needed. The pre-processing includes a workflow of tasks (a.k.a. data wrangling (Bogatu et al., 2019), data processing/preparation pipeline (Konstantinou & Paton, 2020; Romero et al., 2020) or ETL (Ali & Wrembel, 2017)). The workflow includes the following tasks: data integration and transformation, data cleaning and homogenization, data preparation for a particular ML algorithm. Based on pre-processed data, ML models are built (trained, validated, and tuned Quemy, 2020). Since the whole workflow is very complex, constructing it requires a deep knowledge from its developer in multiple areas, including software engineering, data engineering, performance optimization, and ML. Thus, multiple works focus on automating the construction of such workflows. This research area is commonly called *AutoML*. It turned to be a hot research area in recent years (Bilalli et al., 2019; Giovanelli et al., 2021; Koehler et al., 2021; Quemy, 2019). (Kedziora et al., 2020) provides an excellent state of the art of this research area.

Other major trends in ML are pointed to by the Gartner report on strategical technological trends for 2021 (Panetta, 2020). Among the trends *AI engineering* is listed. It is defined as means to “facilitate the performance, scalability, interpretability and reliability of AI models”. Interpretability and reliability is crucial, since AI systems are typically applied to support decision making by providing means of prediction models and recommendations, which by definition must be reliable. Moreover, a decision maker must be able to figure out and understand how a decision was reached by a given model.

Unfortunately, models built by ML algorithms may be difficult to understand for a user, for two main reasons. First, a model may be too complex to be understood by a user. Second, a user typically has access to an input and output of a model, i.e., internals of the model are hidden. Such models are typically referred to as *black-box models*. They typically include ensemble models produced by classification techniques (e.g., Random Forest, Bagging, Adaboost) and ANN models. Even a simple classification model may be difficult to understand if a decision tree is large. ANN models are by their nature non-interpretable (e.g., an ANN with a hundred of inputs and several hidden layers). As a consequence, a user is not able to fully understand how decisions are reached by such complex models (Du et al., 2019).

Yet, in a decision making process, it is necessary to understand how a given decision was reached by a ML model. Therefore, there is a need for developing methods for explaining how ML black-box models work internally. As the response to this need, the so-called *Explainable Artificial Intelligence* (EAI) (Biggio et al., 2021; Goebel et al., 2018; Liang et al., 2021; Langer et al., 2021; Miller, 2019) or *Interpretable Machine Learning* (IML) (Du et al., 2019) techniques are being developed. This research problem is defined as “investigating methods to produce or complement AI to make accessible and interpretable the internal logic and the outcome of the model, making such process human understandable” (Bodria et al., 2021). Explaining ML models turned out to be crucial in multiple business and engineering domains, such as system security (Mahbooba et al., 2021), health care (Danso et al., 2021), chemistry (Karimi et al., 2021), text processing (Moradi & Samwald, 2021), finance (Ohana et al., 2021), energy management (Sardianos et al., 2021), and IoT (García-Magariño et al., 2019).

A substantial growth of this research topic is observed in years 2018-2019. The DBLP service[2] includes in total 215 papers on EAI and 163 papers on IML (as of September 25, 2021). Google Trends[3] shows an increasing popularity trend of this research topic. Figure 1 shows an aggregated trend for EAI and IML.

Techniques for building interpretable ML models can be divided into two categories, namely intrinsic and post-hoc. An orthogonal classification divides the techniques into global and local interpretable models (Du et al., 2019).

Models from the *intrinsic interpretability* incorporate interpretability directly to their structures, making them self-interpretable. Examples of such models include for

[2] https://dblp.uni-trier.de/

[3] https://trends.google.com/trends/

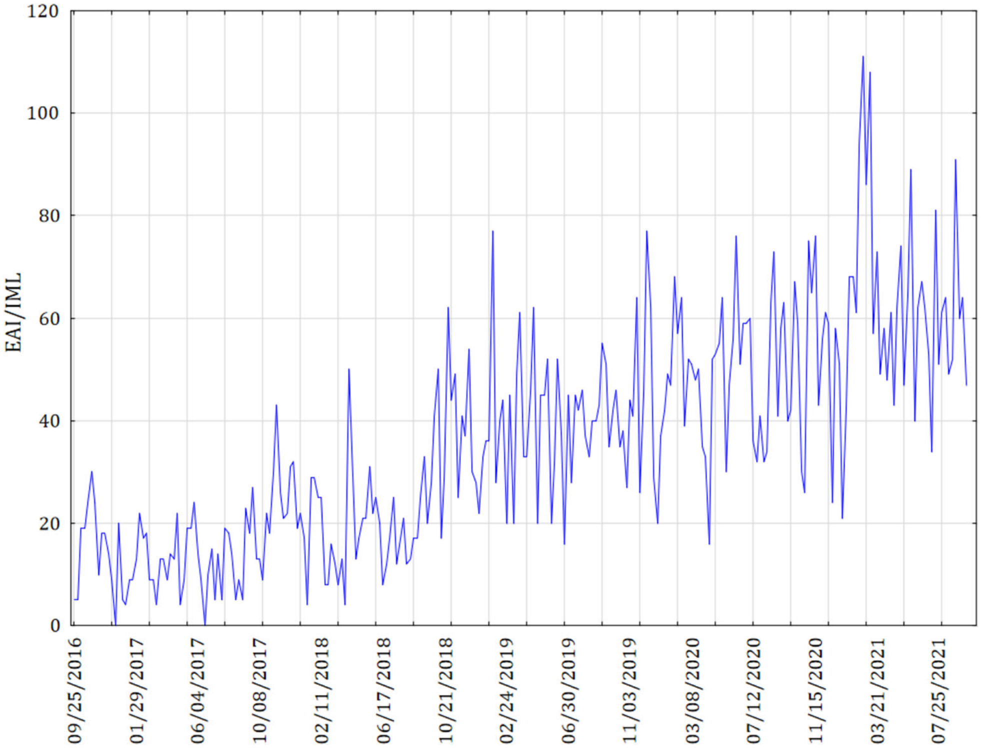


Fig. 1 Aggregated popularity trend of EAI and IML topics (Google Trends)

example: decision trees, rule-based models, and linear models. Models from the *post-hoc interpretability* require constructing an additional model, which provides explanations to the main model.

A *globally interpretable* model means that a user is able to understand how a model works globally, i.e., in a generalized way. A *locally interpretable* model allows a user to understand how an individual prediction was made by the model.

Multiple approaches to explaining models have been proposed. They may be specific to a type of data used to build a model, i.e., there are specific approaches for table-like data, for images, and for texts.

For explaining models that use table-like data, the most popular method is based either on rules or on feature importance. A *rule-based* explanation uses decision rules understandable by a user, which explain reasoning that produced the final prediction (decision). A *feature importance* explanation assigns a value to each input feature. The value represents the importance of a given feature in the produced model.

For explaining models that work on images, the most frequently used technique is called the *Sailency Map* (SM). The SM is an image where a brightness and/or color of a pixel reflects how important the pixel is (it is typically visualized as a divergent color map). This way, it can be visualized whether and how strongly a given pixel in an image contributes to the given output of a model. The SM is typically modeled as a matrix, whose dimensions are the sizes of the image being analyzed.

A concept similar to SM can be used to explain models that work on text data. When the SM is applied to a text, then every word in the text is assigned a color, which reflects the importance of a given word in the final output of a model.

An excellent overview of explanation methods in ML for various types of data is available in Bodria et al. (2021).

3 Special Section Content

This editorial paper overviews research topics covered in this special section of the Information Systems Frontiers journal. The special section contains papers invited from the 24th European Conference on Advances in Databases and Information Systems (ADBIS).

3.1 ADBIS Research Topics

The ADBIS conference has been running continuously since 1993. An overview of ADBIS past and present activities can be found in (Tsikrika & Manolopoulos, 2016) and at http://adbis.eu. ADBIS is considered among core European conferences on practical and theoretical aspects of databases, data engineering, data management as well as information systems development and management. In this context, the most frequent research topics addressed by researchers submitting papers to ADBIS within the last ten years include: *Data streams*, *Data models and modeling*, *Data cleaning and quality*, *Graph processing*, *Reasoning and intelligent systems*, *On-Line Analytical Processing*, *Software and systems*, *Ontologies and RDF*, *Algorithms*, *Indexing*, *Spatio-temporal data processing*, *Data integration*, *Query language and processing*, *Machine Learning*.

All research topics covered within the last 10 editions (years 2012-2021) of ADBIS are visualized in Fig. 2. We constrained the analysis to the 10-years period in order to reflect the recent research interests. Moreover, we analyzed papers published only in the LNCS volumes, to include the highest quality papers. In Fig. 2, the Y axis shows a total number of papers addressing a given topic (the median is equal to 7). Q1-Q4 represent the first, second, third, and fourth quartile, respectively.

The papers included in this special section address topics from Q3 and Q4, and thus represent **frequent ADBIS topics**. These papers cover: *Graph processing*, *OLAP*, and *Machine Learning* (marked in black in Fig. 2). These three topics are outlined in Section 2, whereas the papers included in this special section are summarized in Section 3. It is worth to note that the most frequent ADBIS topics reflect world research trends and they follow research topics of top world conferences in databases and data engineering, including SIGMOD, VLDB, and ICDE (Wrembel et al., 2019). This special section includes three papers covering: *Graph processing*, *OLAP*, and *Machine Learning*.

3.2 Papers in this Special Section

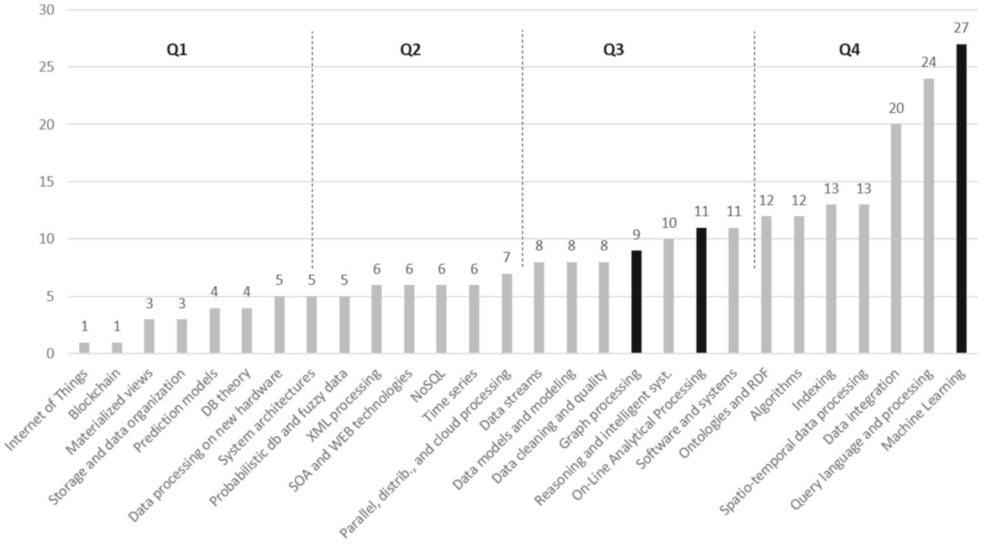
The **first paper** (Belayneh et al., 2022), *Speeding Up Reachability Queries in Public Transport Networks Using Graph*, authored by Bezaye Tesfaye Belayneh, Nikolaus Augsten, Mateusz Pawlik, Michael H. Böhlen, and Christian S. Jensen, addresses the challenges discussed in Section 2.1 for a special case of temporal road networks graphs and a special case of queries, namely, reachability queries over public transport network.

An evaluation of such queries involves multiple computations of shortest paths with additional temporal constraints. Specifically, the connection time calculated as a difference between a departure of the outgoing vehicle and an arrival of previous incoming vehicle is added to the length of a path. The problem is, in general, NP-hard. Therefore, an approximate algorithm is needed to solve the problem efficiently. To this end, the authors propose an algorithm based on graph partitioning: the problem is split into smaller problems. A set of boundary nodes is pre-calculated for each partition. The shortest path is found in each partition (called a cell in the paper) and a choice of a path between partitions. Pre-calculated paths inside cells constitute an index that significantly speeds up the search. In the proposed evaluation, the search is limited to startpoint and endpoint cells and search for chains of cells, as the paths inside cells and boundary nodes are pre-calculatied. The partitioning provides locality, but of course actual performance depends on the choice of partitioning algorithm. The paper contains deep performance analysis and comparison of different partitioning algorithms.

The **second paper** (Francia et al., 2022), entitled *Enhancing Cubes with Models to Describe Multidimensional Data*, by Matteo Francia, Patrick Marcel, Veronika Peralta, and Stefano Rizzi, presents a first step toward a proof of concept of the Intentional Analytics Model (IAM).

IAM mobilizes both Online Analytical Processing (OLAP) and various machine learning methods to allow users express the so-called analysis intentions and obtain the so-called enhanced (annotated) data cube. Analysis

Fig. 2 Research topics within the last 10 years of ADBIS (based on papers published only in LNCS volumes)



intentions are expressed with five operators. The paper focuses on formalizing and implementing the *describe* operator, which describes cube measures. Enhanced cube cells are associated with interesting components of models (e.g., clustering models) that are automatically extracted from cubes. For example, cells containing outliers can be highlighted.

Moreover, the authors propose a measure to assess the interestingness of model components in terms of novelty, peculiarity and surprise during the user's data navigation. A dataviz is also automatically produced by a heuristic to depict enhanced cubes, by coupling text-based representations (a pivot table and a ranked component list) and graphical representations, i.e., various possible charts. Eventually, the whole approach is evaluated through experiments that target efficiency, scalability, effectiveness, and formulation complexity.

The **third paper** (Ferrettini et al., 2022), entitled *Coalitional Strategies for Efficient Individual Prediction Explanation*, by Gabriel Ferrettini, Elodie Escriva, Julien Aligon, Jean-Baptiste Excoffier, and Chantal Soulé-Dupuy, addresses the problem of explaining machine learning models. The goal of this work was to develop a general method for facilitating the understanding of how a machine learning model works, with a particular focus on identifying groups of attributes that affect a ML model, i.e., a quality of prediction provided by the model.

A starting point of the investigation is an observation that attributes cannot be considered as independent of each other, therefore it was required to verify the influence of all possible attributes combinations on the model quality. The influence of an attribute is measured according to its importance in each group an attribute can belong to. A complete influence of an attribute now takes into consideration its importance among all the possible attribute combinations. Computing the complete influence is of exponential complexity. For this reason, efficient methods for finding influential groups are needed.

In this context, the paper describes a method for identifying groups of attributes that are crucial for a quality of a ML model. To this end, the authors proposed the so-called *coalitions*. A coalition includes these attributes that influence a ML model. In order to identify coalitions, the authors proposed to use the following techniques:

- *Model-based coalition*, where interactions between attributes used in a model are detected by analyzing the usage of the attributes by the model. To this end, the values of attributes in an input data set are modified and it is observed how the model predictions vary.
- *PCA-based coalition*, where the PCA method is applied to create a set of combined attributes, represented by a new attribute obtained from the PCA. This set is considered as an influential group of attributes.
- *Variance inflation factor-based coalitions*, where the standard variance inflation factor (VIF) is an estimation of the multicollinearity of the attributes in a dataset, w.r.t. a given target attribute. VIF is based on the R coefficient of determination of the linear regression. Since the value of VIF is computed by means of a linear regression, this method is suitable for coalitions where linear correlation between attributes exist.
- *Spearman correlation coefficient-based coalition*, which takes into account non-linear correlations between attributes. The correlations are computed between all pairs of attributes and their correlations are represented by the Spearman coefficient.

These methods were evaluated by excessive experiments on multiple data sets provided by openml.org, for two classification algorithms, namely Random Forest and Support Vector Machine. As the baseline, the so-called *complete* method was selected. The obtained results, show that the proposed methods provided promising performance characteristics in terms of computation time and model accuracy.

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Jérôme Darmont is full professor of computer science at the University of Lyon, France. He received his Ph.D. in 1999 from the University of Clermont-Ferrand II, France, and then joined the University Lyon 2 as an associate professor. He became full professor in 2008 and has been director of the ERIC research center from 2012 to 2021. In 2017, he was made Honoris Causa professor at Simon Kuznets Kharkiv National University of Economics, Ukraine. He is currently adjunct director of the Institute of Communication at University Lyon 2. His research interests mainly relate to data management performance (performance optimization, auto-administration and benchmarking of databases, data warehouses, data lakes, data meshes...) and cloud business intelligence (data security, query performance and cost, personal BI, big data analytics, textual document analysis...).

Boris Novikov (DSC) is currently a full professor, the Department of Informatics at National Research University Higher School of Economics (HSE University) in Saint Petersbirg, Russia. He graduated from Leningrad University (school of mathematics and mechanics) in 1972 and joined Operations Research laboratory at the same university (Saint-Petersburg University since 1991). Professor since 2000, department chair in 2013-2018 at Saint Petersburg University. Boris Novikov joined National Research University "Higher School of Economics" in jan. 2019. Visited CRAI (Italy) and Aalto University (Finland), was a leading researcher for several projects funded by INTS and Russian agencies, as well as industrial partners. He is a member of journal editorial boards of "Programming and Computer software" and "Computer Science and Information Systems", served as a program committee chair for several international conferences. Research interests are in a broad area of information management and include several aspects of design, development and tuning databases, applications, and database management systems, as well as distributed scalable systems for stream processing and analytics.

Robert Wrembel (PhD, Dr. Habil.) is an associate professor in the Faculty of Computing and Telecommunications, at Poznan University of Technology (PUT), in Poland. Specializes in databases and data warehouses; in the past involved in 8 research and 7 industrial projects in the area of data processing technologies; currently at PUT leading a project for the biggest Polish bank; currently external research expert in the French SupeRob ISITECAP20-25 project and in the DOGO4ML project supported by Ministerio de Ciencia e Innovación - Agencia Estatal de Investigación (Spain); visiting scholar in BI company Targit (USA) (2013); consultant at software house Rodan Systems (2002-2003); lecturer at Oracle Poland (1998-2005); PUT coordinator of Erasmus Mundus Joint Doctorate Information Technologies for Business Intelligence - Doctoral College (2013-2020). Visited numerous research and education centers, including: Universitat Politècnica de Catalunya - BarcelonaTech (Catalunya), Université Lyon 2 (France), Université de Tours (France), Universidad de Costa Rica (Costa Rica), Klagenfurt University (Austria), University of Maribor (Slovenia), Loyola University (USA), INRIA Paris-Rocquencourt (France), and Université Paris Dauphine (France). In 2010 received IBM Faculty Award for highly competitive research, in 2019 - IBM Shared University Research Award, and in 2019 - International Federation for Information Processing (IFIP) Service Award; represents Poland in IFIP Technical Committee TC 2 - Software: Theory and Practice; a chair of IFIP Working Group 2.6 (Database); a regular editorial board member of Data & Knowledge Engineering. In 2021 he has been honored with the designation of ACM Senior Member.

Ladjel Bellatreche is a full professor at National Engineering School for Mechanics and Aerotechnics (ISAE-ENSMA), Poitiers, France. He leads the Data and Model Engineering Team of the Laboratory of Computer Science and Automatic Control for Systems (LIAS). He is also part time professor at Harbin Institute of Technology - HIT (China) since 2019. His was a visiting professor of the Québec en Outaouais - Canada (2009), a visiting researcher at Purdue University - USA (2001) and Hong Kong University of Science and Technology, China (1997-1999). His research interest focuses on Data Management Systems and Semantic Web. He serves as an Associate Editor of the Data & Knowledge (DKE) Journal, Elsevier.