Journal of Visual Language and Computing

journal homepage: www.ksiresearch.org/jvlc/

Decision Support Enhancement Through Big Data Visual Analytics

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ARTICLE INFO

Article History:
Submitted 2.9.2023
Revised 3.20.2023
Accepted 4.2.2023

Keywords:
Decision Support
Big Data
Visual Analytics
Internet of Things

ABSTRACT

The development and diffusion of Internet of Things, Artificial Intelligence, Business Intelligence and Visual Analytics solutions has brought new paradigms to exploit Big Data analytics into Decision Support Systems. The increasing requirements of automating Decision Support Systems and making them more efficient and reliable represent a research field which has recently attracted a lot of interest and efforts. The main challenges are represented by the initial black-box nature of machine learning and deep learning methods, which often cannot deal with the necessity to provide explainable results, which is a critical aspect when dealing, for instance, with automated decision processes in legal and administrative contexts. This paper presents a study of the main concepts and requirements for enhancing Decision Support through big data visual analytics, presenting the Snap4City solution and describing some real use cases in which it has been and is currently being exploited.

1. Introduction

The recent advances in ICT related to Big Data, Internet of Things (IoT) and Artificial Intelligence (AI) solutions have provoked a great interest in investigating the possibility to enhance and improve automatic decision-making processes. The enhancement and automation of Decision Support Systems (DSS) are more and more required in several different contexts (smart city and related domains, industry 4.0, etc. [1]) for a wide range of scenarios and use cases (e.g., public administrations and municipalities, private companies, and regular citizens).

The implementation of DSS based on a model-driven approach has to face the high complexity of many different real use case decision problems, which consequently rely in a large variety of different models. Therefore, it can be difficult to provide suitable and reliable models supporting the automation of the specific decisional process.

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Data-driven decision-making is the process of using evidence and insights derived/learnt from data to guide the decision-making process and to verify a plan of actions before it is committed. In the era of Big Data, this approach is being more and more frequently adopted, and it has been observed that the confluence of data analytics with Big Data can significantly improve the way DSS can be designed and implemented, and how this approach can impact on a company's performance [2]. Big Data Analytics is a way to refer a comprehensive approach to process and analyze big data sets by applying advanced analytics techniques, improving data-driven decision making and support [3]. However, data-driven decisions are still prone to errors and failures, as addressed in [4], in which it is discussed the case of decisions addressed for COVID-19 forecasting, which have often failed, due to several factors such as the small number of input data, lack of historical data as reference. Actually, the quality of decisions depends not only on data, but also on the way in which the data is collected and processed [5]. Furthermore, the automation of data-driven decisions or even the automated suggestions still remains debatable, and there are many examples in literature about issues and causes of failures of data-driven automated decision

DOI reference number: 10-18293/JVLC2023-N1-026

making and supports [6].

In [7], it is highlighted how incorrect decisions, generated/suggested by the automated decision systems in the Swedish public employment service, enforce the evidence that human users have to cover an active role in the decision-making process. In [8], mistakes are reported in the automated Finnish tax assessment process, and this remarks how Explainable AI techniques and methods (e.g., explainability and accountability) are important and should be considered for automated decisions in legal/administrative contexts. In [9], the lack of reliable and accurate evidence in data-driven decisional process at Royal Dutch Shell Telecommunications company led to many problematic decisions. This implies that the quality and amount of data affect the decisions. In addition to this, the same study reports that human decision makers often received more information than they could process, addressing the aspect that human decision makers have a limited capacity for processing data on their own, and therefore DSS are greatly required. Authors in [10] present the case of Danish Primera Air, where the inability of the company to capture big data and use Big Data Analytics for strategic decisions led to the company failure. This event represented a strong motivation towards the adoption of efficient and reliable Big Data platforms.

In this paper, the evolution of DSS and their application in the context of big data platforms for smart city is reported. The paper is focused on the main evolution performed in Snap4City platform to support the design and the implementation of smart applications and DSS. Snap4City is an open-source platform deployed and used in several smart city and industry 4.0 installations. The biggest installation of the framework is a multi-tenant platform, managing advanced Smart City IoT/IoE applications with 20 organizations, 40 cities and thousands of operators and developers. Snap4City is an official FIWARE platform and solutions, it is compliant with security and privacy aspects [18], [20], and provide support for the development of a large range of ML and AI solutions, including what-if analysis and DSS.

The paper is structured as described in the following: in Section 2, the main concepts and requirements for building efficient AI-based Big Data Analytic solutions for decision support are reported. Section 3 presents the proposed solution, the Snap4City framework, which include an ML/AI enabled Big Data Analytic platform for decision support. Section 4 reports some real use cases implemented in the Snap4City platform. Finally, Section 5 is left to conclusions.

2. AI-based Big Data Analytics: Concepts and Requirements

Descriptive, prescriptive and predictive solutions have been provided since many years, from statistic, operating research, and regressive models. In most cases, they have not been capable to provide satisfactory results for their limitation of discovering/modelling complex functions and relationships. Early Machine Learning (ML) and Deep Learning (DL) solutions mainly had a black box nature which needed explainability and interpretability before their effective application in real-world cases and critical situations [11]. On the other hand, ethical aspects (on data and processes) are very sensitive and a wrong assumption in taking data and/or setting up solutions may lead to biased results/suggestions, which may correspond unfairness, discriminations, and this may lead to unforeseen costs [12]. The IoT (Internet of Things) combined with Big Data are enabling a large number of new data analytics. Big Data Analytic with AI play a strong role in leveraging businesses and solutions providing reliable predictions, prescriptions, early warning, classifications, detections, suggestions, etc., thus enhancing automated/semi-automated decision support processes. Actually, these technologies can lead to reduce costs and increase the efficiency of business and production processes. This also implies to add value to collected Big Data, extracting from them new knowledge, hints, strategies, mitigations, and discovering information and implications never detected before.

2.1 Context and Application Scenarios

The applications of the above-described aspects can be experienced in almost any domain of smart city and industry: mobility, health, energy, environment, waste, chemistry, manufactory, delivering, agriculture, etc. The resulting advantages can be for final users, for decision makers and thus for city/companies. For example, the efficient parking prediction models and tools (smart mobility) [13] allow to reduce the social cost of parking search, in terms of reduction of fuel consumption, producing less NO2 and other pollutants. Optimization of services such as waste collection (smart environment), which implies a cost reduction by reducing the number of trucks/trips needed for waste collection. This is an advantage for the quality of life of city users, and a reduction of costs for the administrators. A second example is related to the predictive maintenance in smart industry, Industry 4.0 [14] for reducing the costs for intervention, due to unexpected faults and stops of the services/productions. Predictive maintenance also implies a further reduction of the production costs by improving company's efficiency and resilience. A third example is related to assess and predict reputation of services (for example: mobility services, restaurants, museum) from social media to increase the quality of services, producing suggestions and thus to reduce pikes in the demand and promote alternative offers and solutions.

Moreover, one of the main common goals of DSS may be to prepare cities and industries to be more resilient to the so called *unexpected unknown* events, natural or provoked disasters, by integrating simulations and ML/AI solutions, enabling what-if analysis in quasi real time, and increasing resilience and capacity. Reacting to unexpected unknown events in faster manner leads to the reduction of the recovery costs, thus mitigating the overall risks and damages.

The most relevant challenges for cities in the coming years include the energy saving and the ecological transitions KPI (Key Performance Indicators), the Sustainable Development Goals (SDG) [15] (reported in Figure 1), promoting more livable cities according to 15 Min City Indexes [24] and Driving Urban Transitions, DUT, to a sustainable future.

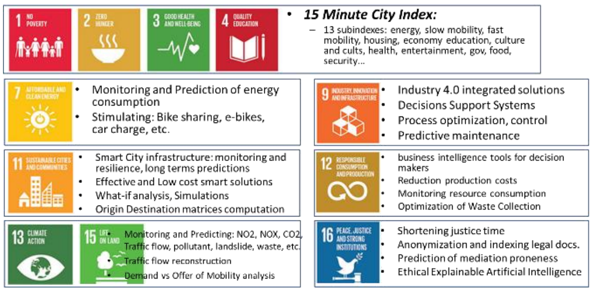


Figure 1: Sustainable Development Goals, a part of them more related to Snap4City Smart City solutions.

The Snap4City platform is an open source framework, developed by the DISIT Lab of the University of Florence (as described in more details in Section 3), aiming at satisfying all the requirements and features described in the following.

2.2 Big Data Analytics and Explainable AI

Big Data Analytics in the last few years rapidly evolved and started to be used in complex systems and not only to make direct predictions and prescriptions.

An efficient framework for supporting decision makers through AI-based Big Data analytic solutions should provide the capability to exploit AI techniques (including: short-term and long-term forecasting and classification models, suggestion and recommendation systems, etc.) to perform system modelling and simulation (based on the different applicative scenarios). The exploitation of these techniques can be used to create solutions for Early warning and what-if analysis. They can be used to define resilience countermeasures, disaster recovery and to build more informed strategies, mitigations and plans. A conceptual overview of these topics is illustrated in **Figure 2**. In this view, a relevant role is played by the formalization of the scenarios, and in the identification of the DSS targets in terms of quality, KPI, SDG, etc.

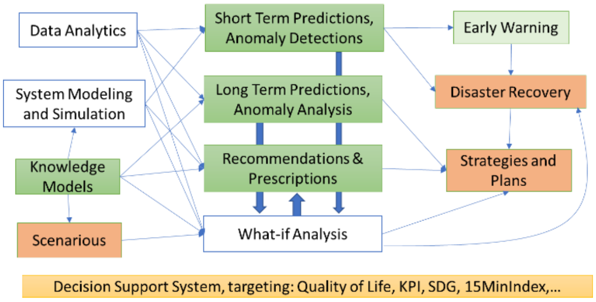


Figure 2: Data Analytics based on AI solutions for decision support systems.

Therefore, Decision Makers started to use the new solutions with the expectation and the strong need of respecting ethics on data and processes. To this end, ML/AI trustworthiness, Data Ethics and AI Ethics approaches have been studied and applied in the context of decision makers [16]. Data Ethics refers to the aspects that may provoke a bias and ethical problems since the training phase. For example, training the AI with biased data, unbalanced distribution of cases, etc. Moreover, specific ML/AI methodologies and solutions for Explainable Artificial Intelligence (XAI), are presently providing support in this direction [17], since they are capable to explain the rationales behind the typical results provided (global explainable AI) and may provide specific description/rational for each result/suggestion provided (local explainable AI). XAI typically adds value to the provided decision producing hints and discovering implications and correlations never detected before. Therefore, as in Snap4City, such an integrated approach including ML/AI trustworthy, Data Ethics and AI Ethics must be enforced into the development process and life-cycle (as depicted in **Figure 3**) of the new smart platforms and solutions.

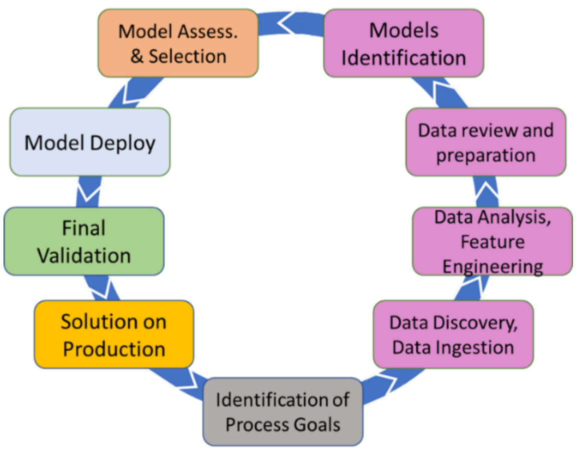


Figure 3: Development life cycle of AI-based smart solutions: adopted/suggested by Snap4City platform.

2.3 Legal Aspects and Privacy

Any ML/AI/XAI solution (including data ingestion, transformation, training, visualization, etc.) has to respect data privacy policies. i.e., being compliant with GDPR [18], [20] (General Data Protection Regulation of the European Commission) and/or similarly regulations in other non-European Countries (e.g., the California Consumer Privacy, CCPA). These aspects have to be addressed since the beginning of the above presented life cycle (see **Figure 3**), when the data discovery and data ingestion are performed, and in particular in the data analysis phase. This also means that the solutions have to respect the Data sovereignty, for which the data are subject to the laws and governance structures of the nation/country where they were collected/produced. Specific licenses can be modelled on Snap4City and related development tools enable the development of AI, while each single implementation has to guarantee the respect of Data sovereignty and GDPR. One of the main problems on AI may be seen as the need of accessing to specific data related to the person behavior, or collective behavior. On the other hand, the state of the art literature and the long track in data analytics also demonstrated that in a large number of cases, surrogated data can be found to substitute those that are protected or too private to be used (in some cases, at the expenses of a small reduction in precision). Specific techniques for anonymization preserving static validity may help in this sense and are getting a larger diffusion.

2.4 Requirements

On the basis of the analysis conducted in the several developments of Snap4City solutions, a list of requirements for enabling AI-based Big Data analytic solutions in decision support systems is proposed. Specifically, In the context of IoT Enabled Smart Cities and Industry 4.0, the European commission has fostered and stimulated the analysis of this kind of requirements, for instance: EIP-SCC (https://eu-smartcities.eu/), the European Innovation Partnership on Smart Cities and Communities; ENOLL (https://www.openlivinglabs.eu/), the European Network of Living Lab, supporting real-life test-bed and experimentation environments. Moreover, the Select4Cities (https://www.select4cities.eu/) consortium was one of the largest pre-commercial procurement, involving the cities of Copenhagen, Antwerp and Helsinki, created to identify the best solutions putting together the smart city context and the living lab and all the defined requirements. Snap4City has been the winner of the Select4Cities PCP in the 2019.

Requirements of IoT-enabled contexts, use cases and scenarios must take into account the complexity due to the increasing number and types of data sources, IoT protocols and brokers. The goal is to aggregate all these kinds of heterogeneous data into well integrated representations and tools for decision support to be provided in some interactive dashboards and visual analytic tools. To this aim, a first important step is represented by data collection and storage, which has to be compliant with all the afore mentioned protocols and formats. Also, semantic storage and triplification is required, to infer and build additional knowledge. Business intelligence tools are important to enable and enhance decision support. Business intelligence may request some data analytics, for example to calculate alternative routes after closing traffic for example in the areas of the city where air quality sensors are giving too high values for pollutant concentration, or for example in the context of smart parking to forecast free slots, for smart waste management to optimize the routes for collecting waste for trucks, etc. Finally, the platform has to provide complete visualization tools. Visualization should be interactive, to send commands from the user interface to the processing back-end, selecting some data transformation to build business intelligence tools.

In the following, a list of the identified requirements for enabling AI-based Big Data analytic solutions in decision support systems is provided:

- **Exploit AI-based Big Data analytics**, as discussed in the previous sub-sections.
- **Provide visual interfaces for users**, e.g., city dashboards, visual applications etc., in order to offer smarter and more accessible services to final users.
- **Data-Driven and Event-Driven approach by enabling IoT solutions**, to have the possibility to implement data-driven applications through the web without the necessity to install local applications, exploiting the development of IoT (the Internet of Things), IoT Edge.
- **Collect historical data** and provide access through API and/or microservices. It is also necessary to build a number of knowledge bases and semantic ontologies that can be queried and navigated, in order to understand what is going on in a specific domain.
- **Serve as Living Lab**, in order to foster open innovation, collaborative work, sharing of data, processes, visualization tools, experiences, solutions. The management of decision-making processes always involve a community of users, organizations and stakeholders.

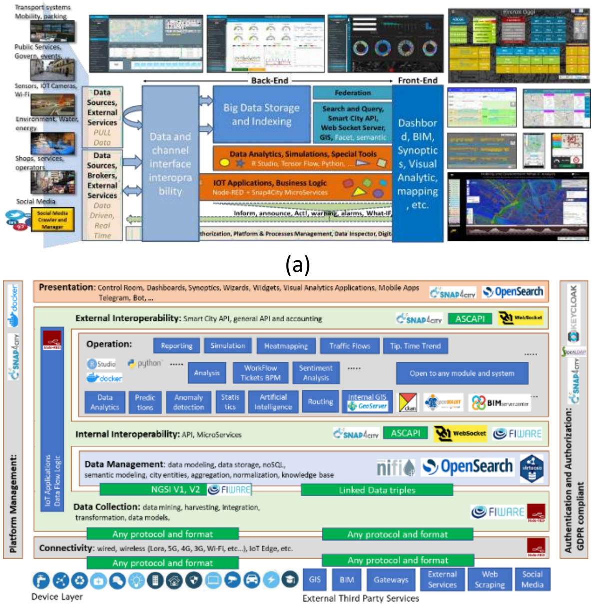
In addition, also the following non-functional requirements have been identified:

- **Open Source**, following the Open Standard for communication and API.
- **Interoperability** regarding different kinds of protocols, formats, internal and/or external API, capable, with the possibility to be open to proprietary protocols as well.
- **Scalability and Robustness**: the architecture should be distributed and decoupled, modular, microservice-oriented.
- **Security by Design**: compliance to HTTPS, TLS standards and global/local regulations.
- **Privacy by Design (User Centric Design)**: compliance to GDPR and other global/local

regulations for data privacy and personal data management.

3. The Snap4City framework

In this section, the Snap4City solution (https://www.snap4city.org/) is presented, with the aim of responding to the requirements previously defined in Section 2. The Snap4City platform allows to collect data of any kind (dealing with most file formats and protocols) to save them into a Big Data store in which they can be queried for recovering specific historical data. The same storage can be used to collect data in real time and to save data analytic results. An overview of the Snap4City architecture is shown in **Figure 4**.



(a)

(b)

Figure 4: Overview of the Snap4City functional (a) and technical (b) architecture.

The general workflow includes the following activities:

- Big Data ingestion (historical and real time data collection and update, data transformation, see the Data Collection and Data Management layers in Figure 4b).
- Big Data Analytics AI/XAI tools, including Data transformation and dataset construction for implementing ML/DL predictive models training and validation (see the Operation Layer in Figure 4b).
- Model execution, taking in input the real time data, and the Model Fit to produce predictions which could be estimated 24 hour in advance and may be used to inform the civil protection, municipality, etc. The resulting model assesses in real time the probability of landslide events as early warning/prediction.
- Visualization of data and results (see the Presentation layer in Figure 4b) by means of visual analytic tools such as Dashboards (exploiting a large variety of graphical widgets), Mobile Apps, etc. Visualization should be interactive, to send commands from the user interface to the processing back-end, selecting some data transformation to build advanced business intelligence tools.

In Snap4City, many different activities of the previously described workflow, such as data ingestion and data analytic processes, are performed by using Node-RED applications on docker containers. The Node-RED visual language and environment allow to create IoT enabled application flows (see the IoT Applications Layer in Figure 4b) that can exploit the platform MicroServices with a specific node.js library [19]. In this way, users can build their own Business Logic supporting data-driven/event-driven paradigms. Data Analytics processes can be developed by using Python and/or Rstudio and be executed through dedicated Node-RED IoT Applications. IoT Apps may also allow to send alerts via Telegrams, SMS, emails, for alerting based on Data Analytics results.

Considering the requirements presented in Section 2.4, Snap4City enables AI-based Big Data Analytics, respecting ethics and GDPR compliant [20]. Snap4City has developed a large number of solutions in the context of Smart City and Industry 4.0 [21], [22], [23], serving as Living Lab by supporting users, developers and organizations to act in the platform at different levels. Snap4City fully supports the development of real time data analytic processes through trustworthy XAI. Snap4City is distributing a number of Open-Source data analytics tools and algorithms for: prediction, anomaly detection, classification, detection, constrained routing, optimization, analysis of demand vs offer of transportation. Data Analytics is fully integrated into What-IF analysis tools in control rooms, defining scenarios and solutions for operators and users.

4. Real Use Cases

The Snap4City framework is largely employed in many real uses cases and scenarios, in a wide number of smart cities, municipalities, industry 4.0 and companies in many different countries in Europe. The solution is applied in several different domains, such as mobility, industry 4.0, tourism management, smart waste and environment, 3D city digital twin representation. In the following, some real uses cases are described.

A data analytics and predictive model use for landslide forecasting has been presented in [21]. In this use case, the Snap4City platform has been used to ingest information from IoT Sensors and Open Data on the kind of terrain, the slope, the amount of cumulated rain, humidity in the Florence metropolitan area (Italy). Several predictive models for early warning have been designed, implemented and applied to collected data features: Random Forest (RF), eXtreme Gradient

Boosting (XGBoost), Convolutional Neural Networks (CNN) and Autoencoders different models have been assessed, and the XGBoost model resulted to be the best in terms of MAE, MSE and RMSE. An overview of this use case is illustrated in **Figure 5**.

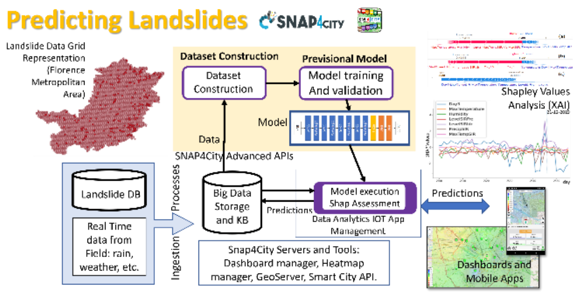


Figure 5: Landslide prediction framework exploiting the Snap4City platform.

Explainable AI tools have then been used to explain why a certain level of risk has been estimated by the predictive model, and which feature has a higher correlation with the result of the prediction. In the specific, Shapley values have been used, which measure the average expected contribution of each single feature with respect to all possible feature combinations. In particular, the features that resulted to contribute most to the prediction of a landslide event are precipitation level, temperature and phreatimetric data.

Another real use case is related to Industry 4.0. In [14], a Deep Learning solution for short term prediction of the working status of the Altair chemical plant has been presented. A DL model based on Long Short Term Memory Neural Networks (LSTM) and CNN has been used to provide one hour prediction of the plant status and indications on the areas in which the intervention should be performed by using explainable AI techniques (i.e., Shapley values showing that the most relevant features in fault determination were the sodium hypochlorite levels and Potable Ferric rate in two different lines of the plant). All data and results are shown in a maintenance dashboard (see **Figure 6**) in which it is possible to see the number of maintenance events in a chosen time period: the average and median of the number of hours needed to complete a maintenance intervention (intended as the difference between the start and end of intervention datetime).

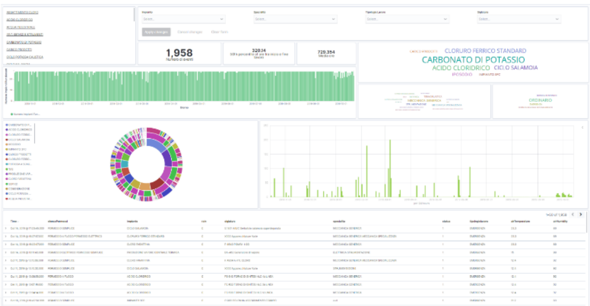


Figure 6: Maintenace Dashboard for Industry 4.0 Business Intelligence.

In [23] a method based on Bidirectional Long Short-Term Memory networks (Bi-LSTM) has been employed to provide predictions of available bikes in bike sharing racks, even with a limited amount of historical data. The solution was validated by using data collected in bike-stations in the cities of Siena and Pisa (Italy). In addition, an analysis of features relevance based on SHAP that demonstrated the validity of the model for different city cluster behaviors.

5. Conclusions

In this paper, a study and analysis of concepts to enhance decision support systems (DSS) through big data visual analytics have been presented. The main results that have been found by reviewing the state of the art, report that model-driven approaches for implementing DSS cannot properly handle the complexity of the many different real-world decision problems it must address. However, relying on data-driven decisions only can also lead to errors and failures, as reported in many use cases described in literature. To improve the effectiveness of DSS and support the Sustainable Development Goals, it is necessary to improve the improve the authority of AI-based decision support, in order to trust and increase the automation level of decision-making processes. To this aim, requirements have been provided in Section 2 of the paper, with a particular focus on discussing aspects such as the integration of Explainable AI in Big Data analytics, the management of legal aspects and privacy issues. In the specific, an efficient framework supporting decision makers through AI-based Big Data analytic solutions should provide the capability to exploit AI techniques to perform system modelling and simulation, easily adapting to different applicative scenarios. This can lead to smarter solutions for Early warning and what-if analysis, improving the environment resiliency, the adoption of countermeasures etc. To this aim, the Snap4City framework has been presented in Section 3, as a proposed solution to address all these aspects. Actually, the platform provides the capabilities to ingest, store and transform Big Data; exploit Big Data Analytics AI/XAI tools for implementing and executing ML/DL predictive models training and validation; visualization of data and results through Dashboards and Mobile Apps. In Section 4, a number of use cases have been also described to validate the proposed solution in real world scenarios and contexts.

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