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Informatics

Implementation of a Prediction Model with Cloud Services

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The paper deals with the prediction model based on heterogeneous matrices, and prediction process is reduced to heterogeneous matrix processing to identify prediction precursors whose joint use increases the probability of the occurrence of the event. This paper proposes the idea of usage of special splits only for certain precursors which makes it possible to use cloud services capabilities for prediction tasks using the heterogeneous matrices as well. Big data systems also include prediction tasks so Azure IoT Hub is used as a managing service, hosted in the cloud, that acts as the central message hub for bi-directional communication between IoT application and the devices it manages. IoT Hub supports communications both from Rigado's Solutions - RuuviTag Device to the cloud and from the cloud to the device. IoT Hub monitoring helps us to maintain the health of our solution by tracking events such as device failures and device connections. *© 2020 Bull. Georg. Natl. Acad. Sci.*

Prediction, big data, IoT Hub, Rigado Device

Big data is structured or unstructured data of huge volumes and diversity as well as the methods for processing them allowing distributed analysis of information. Big data analysis is carried out in order to obtain new, previously unknown information [1,2]. One of the tasks of big data is that analytics and prediction are based on the processed and structured information.

In the present paper we discuss the performance of the prediction task using heterogeneous matrices. The prediction process is then processed into a matrix to identify such precursors among all the precursors whose joint use increases the probability of an event occurrence. Only for dedicated precursors special splits can be used which enable new, cloud-based services to be used for prediction tasks as well [3-5].

Prediction Using Heterogeneous Matrices

Let us consider prediction tasks that include many fields such as business, macroeconomics, weather forecasting, election results, sports competitions, finances, crime and prediction of seismic activity: earthquakes, volcanoes and tsunamis, as well as flood risks.

Complex and statistics based models for all these fields do not always appear to be as accurate as simple models. However, it should also be taken into account that the combining models or computational predictions obtained from different models on average increases the prediction accuracy. However, as the prediction horizon increases, the prediction accuracy decreases [6,7].

Predictive systems can use parallel data [8, 9], which is a single event-dependent data set that exists at different time (parallel by time) or location (parallel by location) and/or additional data. In practice, parallel data can be used to effectively solve earthquake or other cataclysm prediction, economics (business, macroeco-nomics), political events forecasting (elections, redistribution of power), medicine, and other fields.

Parallel data can consist of new types of predictive processes – extended heterogeneous matrices [5-9] which are used to generate and process parallel data.

The matrix, which fits into the business-predictive process model, is dynamically changing, which means it can be resized over time. The matrix is constantly filled from top to bottom with the addition of new data, the number of columns fluctuating, the data being added or deleted in accordance with the purpose function. It is also possible to expand the matrix below – data will be added, according to old, current events or archive data. The main feature is that this matrix constantly makes prediction for the given moments of time. Such a process allows for dynamic prediction.

The Dynamic Model of Prediction

In this paper, we describe an algorithm that can be formulated as follows: (a) For the given prediction task, we present several dynamic models that use different prediction methods; b) We evaluate and rank models; c) We select combinations of models (two, three, etc.). Evaluations and selections of combinations are done according to parallel probabilities.

During the prediction task, we call the dynamic a model that implies a consistent, continuous, constant prediction for some time periods, such as daily, monthly, etc., for a discrete time. Such are the economic forecasting tasks. For example, currency exchange forecasting (specifically for Georgian GEL).

Each event that influences event prediction is represented as a separate data vector. In the name of the matrix, the word "conditional" means that it is not known in advance how many events pre-dicted the prediction (i.e., how many vector data are included in the matrix). Some events (and corres-ponding vectors) are removed, some are added, and some are moved to another location of the matrix. The word "timestamp" is used because the number of the vector row depends on the time. In each vector, the data is arranged according to time.

Of course, each business forecasting task may have an extended matrix for one territorial region, but it may be possible for a certain forecasting task to have an extended matrix that will be constructed over a period of time.

The new algorithm can be formulated as follows: Different dynamic models using different prediction methods can be built, then the models can be evaluated and ranked and combinations of models (two, three, etc.) can be selected that together increase the probability of occurrence. In Fig. 1 t1, t2, t3,... denote time periods, while PR1, PR2, PR3,... denote different prediction methods:

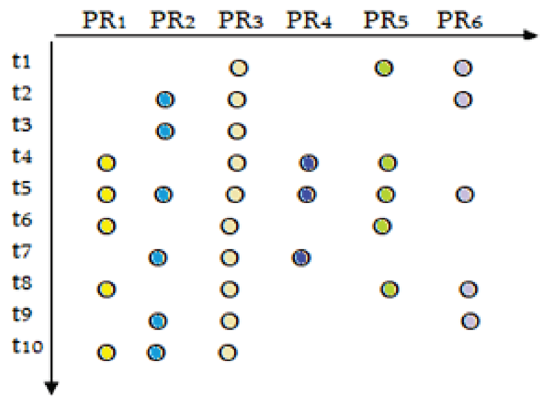

Fig. 1. Possibility to make different predictions.

Our main goal is to distinguish prediction methods from those methods (precursors) that in the combined usage increase event occurrence probability and special splits can be used for them in order to allow new, cloud-based services to be used for prediction.

For our example shown in Fig. 1 these methods are:

For the time t1: PR3, PR5, PR6.

For the time t2: PR2, PR3, PR6.

For the time t3: PR2, PR3.

For the time t4: PR1, PR3, PR4. PR5, etc.

For the moment t5: All is 1, and this time an earthquake occurred actually.

Here the lowest intersection has methods PR1 and PR4.

The accuracy of each prediction method is much lower, and the coupled PR1 and PR4 on the prediction are higher than on a separate basis, and the "expenditure" on the prediction is within the allowed budget.

Consider how cloud services can be used for prediction tasks. We have chosen Microsoft's Azure IoT Hub system for real-time data gathering [11-12], processing and analysis of the prediction.

Collect, Store, Analyzing Data in Real Time

The internet of things, or IoT [13], is a system of interrelated computing devices, mechanical and digital machines, objects, animals or people that are provided with unique identifiers (UIDs) and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction.

We use Azure IoT Hub to build IoT solutions with reliable and secure communications between IoT devices and a cloud-hosted solution backend [14-15]. We can connect virtually any device to IoT Hub.

IoT Hub supports communications both from the device to the cloud and from the cloud to the device. IoT Hub supports multiple messaging patterns such as device-to-cloud telemetry, file upload from devices, and request-reply methods to control our devices from the cloud [16-17].

IoT Hub monitoring helps us maintain the health of our solution by tracking events such as device creation, device failures, and device connections. IoT Hub's capabilities help us build scalable, full-featured IoT solutions such as managing industrial equipment used in manufacturing [18-19], tracking valuable assets in healthcare, and monitoring [20-22] office building usage.

Fig. 2 presents an IoT Hub named Nino and Steam Analytics job named Testing on Microsoft azure portal create.

We use Rigado's Solutions – RuuviTag that is an advanced open-source sensor beacon platform designed to fulfill the needs of business customers, developers, makers, students, and hobbyists. The device is a Bluetooth LE beacon with an environment sensor and accelerometer built in (Fig.3). RuuviTag communicates over BLE (Bluetooth Low Energy) and requires a gateway device to talk to Azure IoT Central.

IoT Hub provided by Microsoft Azure that can be used to connect, provision and manage IoT devices; communicating large amounts of data per month. IoT Hub acts as a bridge between devices and their solutions in the cloud, allowing us to store, analyze and act on data in real time.

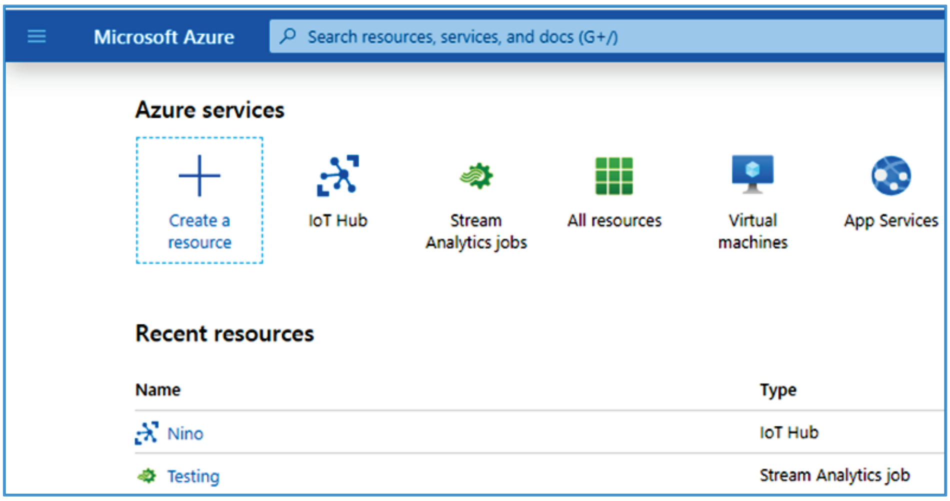

Fig. 2. Iot Hub and Steam Analytics job in Azure Portal.

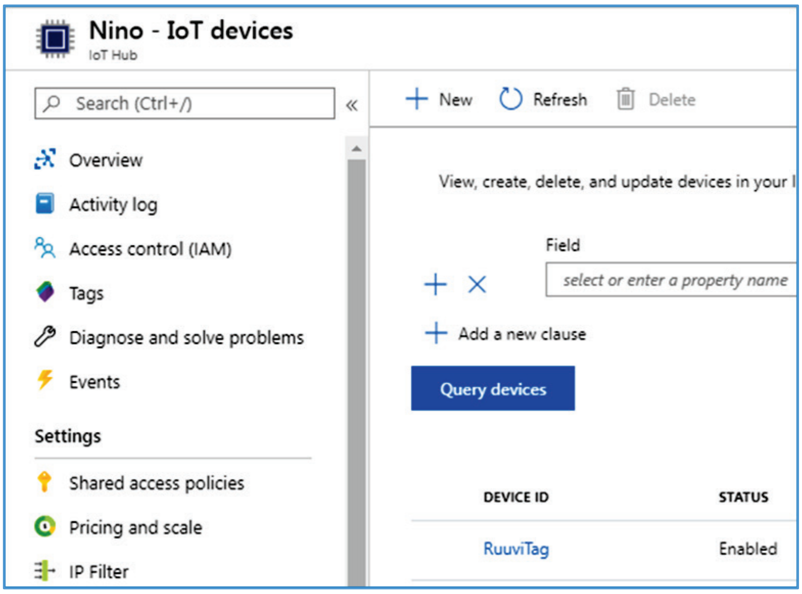

Fig. 3. RuuviTag connected to Iot Hub.

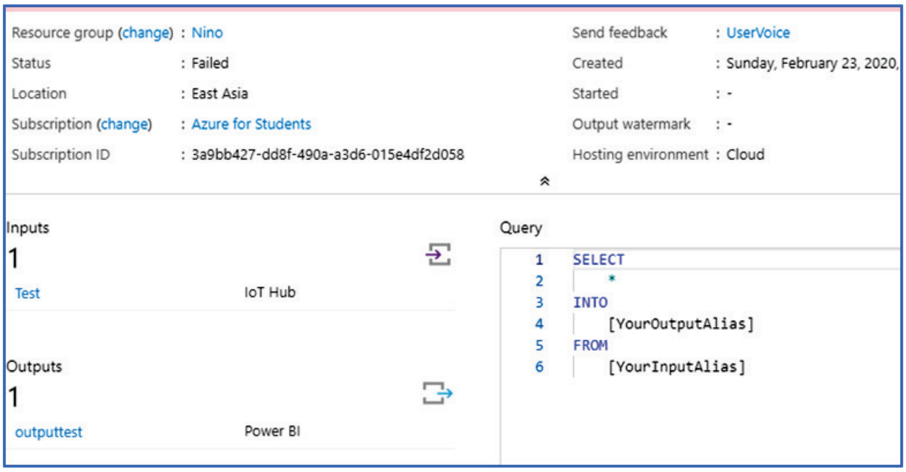

Fig. 4. Inputs and Outputs of RuuviTag sensor.

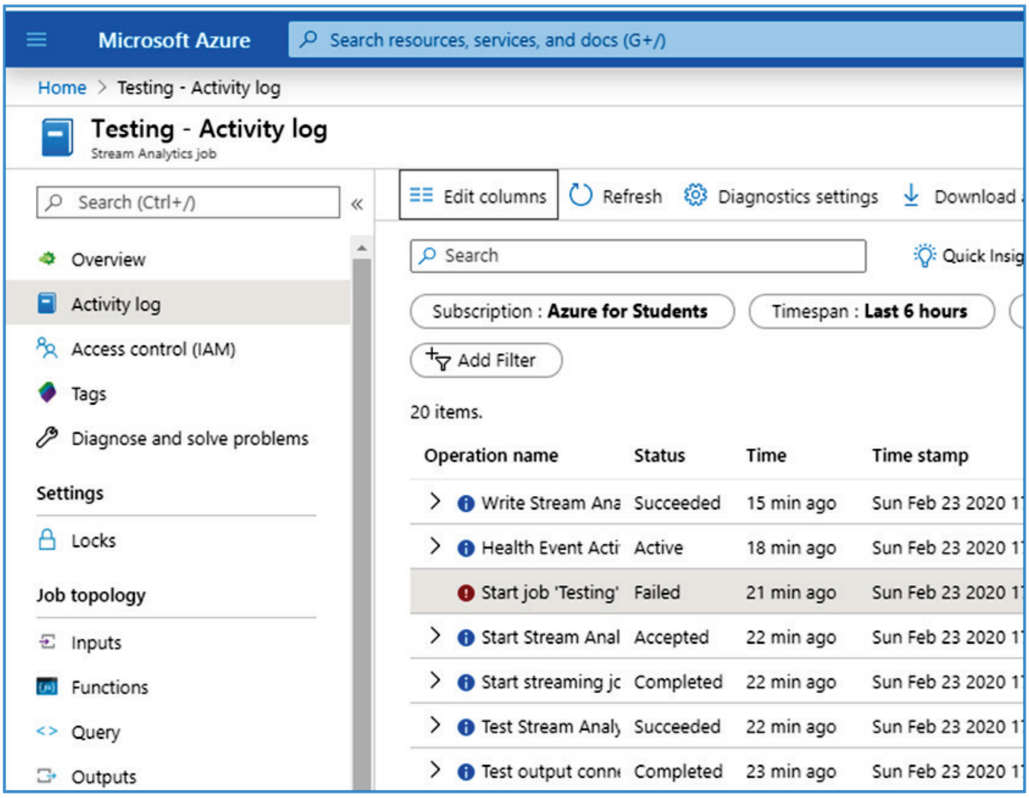

Fig. 5. Activity Log of Testing.

Fig. 4 shows test mode, fixed input (Inputs) and one output (Outputs) attempt. Platform logs (Fig. 5) provide detailed diagnostic and auditing information for Azure resources and the Azure platform they depend on. They are automatically generated although we need to configure certain platform logs to be forwarded to one or more destinations to be retained.

Conclusion

In the paper examples of the usage of parallel data for dynamic forecasting models are presented. An algorithm is defined that allows finding pairs of models that together with higher probability determine the event prediction. Azure IoT is used as a Hub to build IoT solutions with RuuviTag devices. Integrating smart technology into model of prediction will enable us to get more communication and information gathering, more accurate data acquisition and better decision.

ინფორმატიკა

პროგნოზირების მოდელის იმპლემენტაცია ღრუბლოვანი სერვისებით

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§ ივანე ჯავახიშვილის სახ. თბილისის სახელმწიფო უნივერსიტეტი, ზუსტ და საბუნებისმეტყველო მეცნიერებათა ფაკულტეტი, კომპიუტერული მეცნიერებების დეპარტამენტი, თბილისი, საქართველო

ნაშრომში განხილულია პროგნოზირების მოდელი, რომელიც ეფუძნება ჰეტეროგენული მატრიცების გამოყენებას. პროგნოზირების პროცესი კი დაყვანილია ჰეტეროგენული მატრიცის დამუშავებაზე, რათა გამოვლენილი იყოს პროგნოზირების წინამორბედების ერთობლიობიდან ის კონკრეტული წინამორბედები, რომელთა ერთობლივი გამოყენების საფუძველზე იზრდება მოვლენის ხდომილობა. ნაშრომში შემოთავაზებულია ნივთების ინტერნეტის (IoT) გამოყენების იდეა მხოლოდ გამოყოფილი წინამორბედებისთვის, რაც იძლევა საშუალებას ღრუბლოვანი სერვისების შესაძლებლობები გამოყენებულ იქნას პროგნოზირების ტიპის ამოცანების გადასაწყვეტად ჰეტეროგენული მატრიცების გამოყენების საფუძველზე. დიდ მონაცემთა სისტემები ასევე მოიცავს პროგნოზირების ამოცანებსაც, ამიტომ Azure IoT Hub გამოყენებულია როგორც მმართველი სერვისი, რომელიც მოთავსებულია ღრუბელში და როგორც hub-ის ცენტრალური მესიჯი მართავს ორმხრივ კომუნიკაციას IoT აპლიკაციასა და მენეჯმენტ მოწყობილობებს შორის. IoT Hub მხარს უჭერს კომუნიკაციებს Rigado-RuuviTag მოწყობილობის გადაწყვეტილებებს ღრუბლამდე და ღრუბლიდან მოწყობილობამდე. IoT Hub-ის მონიტორინგი დაგვეხმარება, რომ უზრუნველყოფილი იყოს სისტემის შეუფერხებელი მუშაობა ისეთ სიტუა-ციებშიც, როგორიცაა მოწყობილობის გაუმართაობა და მოწყობილობებთან დაკავშირების პრობლემები.

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