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Fog computing architecture for personalized recommendation of banking products

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ABSTRACT

In this article, a novel Fog Computing solution is proposed, developed in the area of fintech. It integrates predictive systems in the process of delivery of personalized customer services for the recommendation of the products of a banking entity. The motivation behind this research is to improve aspects of customer support services, especially, achieve greater security, increased transparency and agility of processes as well as reduce entity management costs. The presented architecture includes fog nodes where data are processed by light intelligent agents allowing for the implementation of contextual recommendation systems together with the configuration of a Case Based Reasoning in the Cloud layer to improve the efficiency of the whole system over the time. The recommendation system is the cornerstone of architecture operating on banking products, such as mortgages, loans, retirement plans, etc., and it is developed by a hybrid method of recommendation: collaborative filtering combined with content-based filtering. The article analyzes the presented architecture while performing a verification and simulation of the data in the context of commercial banking. For this purpose, it shows the use of the proposed system of recommendations that represent the different communication channels as well as the possible devices. The proposed architecture offers the opportunity to improve the customer service in the bank's physical channels and at the same time generate technological support to improve the resolution capacity of office managers, allowing employees to adopt a more versatile and flexible role. It also allows the evolution of the banking services model in offices while the processes that support it to follow a one-stop shop approach.

1. Introduction

Some sectors of the finance industry offer web-data based products and services which cannot be obtained from a bank or a similar provider. This results in a new and competitive environment. The products of the new players range from digital payment solutions and information services, savings and deposit taking, to modern services such as online banking, multi-channel advice and securities trading, not to mention financing solutions (Dapp, 2014). The financial industry is conscious of the need to apply technology to improve its activity; this is reflected in the coinage of the term Fintech or Financial technology, used to denominate the use of computer programs and other technology that supports or enables banking and financial services. In general, the current trend in Fintech developments includes online credits, risk analysis and the treatment of large volumes of data. However, we have detected a lack of technological solutions in the field of commercial banking and personal finance management services which would contribute to improved customer services in financial institutions. In view of this new landscape of solutions that require the capture and processing of a massive volume of data, we propose the use of Fog computing developments.

1.1. Fog computing as a solution in commercial banking

Fog computing emerges as a new computational paradigm that extends the services of Cloud computing to the edge of the network (Networking Index, 2016), Local resources are not all sent to the cloud, instead the computing, communication, control and

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storage occur locally; closer to the end users (Datta, Bonnet, & Haerri, 2015). The benefits of this feature include low latency, mobility, network bandwidth, security and privacy. The OpenFog Consortium, (OpenFog Consortium Architecture Working Group, 2017), is a group of vendors and research organizations advocating for the advancement of standards in this technology, they proposed the Architecture Working Group. Founded in November 2015 by ARM, Cisco, Dell, Intel, Microsoft and Princeton University have created the OpenFog Reference Architecture.

Fog computing is the result of technological convergence, it responds to the new requirements that have arisen due to the ubiquity of devices and the demands for a more agile management of networks and services, and for data privacy (Vaquero & Rodero-Merino, 2014).

According to the authors (Hajibaba & Gorgin, 2014) the following attributes characterize Fog computing:

(i) Proximity of data to end users. Information is no longer hosted in large data centers away from the customer, instead it is located closer to the end user, improving latency and access.
(ii) Hierarchical organization. The architecture is organized in multiple levels to support low latency and scalability.
(iii) Edge location, location awareness, low latency: the data generated by the devices and sensors are acquired from Fog collectors. This provides location and provides low latency and context awareness (Bonomi, Milito, Zhu, & Addepalli, 2012).
(iv) Wide geographical distribution. Geographical distribution contributes to faster data analysis and a better support for location-based services. Load balancing algorithms can also be sued to improve the computation capabilities of the fog (Al-khafajiy et al., 2019a; Mostafa, Al Ridhawi, & Aloqaily, 2018).
(v) Extensive sensor network and a large number of nodes. Fog computing uses a large scale sensor network to monitor the environment.
(vi) Support for mobility. Host-managers can control how users access without having to scroll the entire WAN, improving user performance, quality of service, security and privacy.
(vii) Real-time interactions. In Fog computing the servers belong to the same network as the end users, therefore, Fog includes interactive applications instead of batch processing and real time data analysis is more frequent in Fog computing.
(viii) Predominance of wireless access. Fog computing fulfills the vision of the Internet of things vision taking into account that it is considered an important objective that the devices that participate in computational tasks using network resources support wireless communication. (Madsen, Burtschy, Albeanu, & Popentiu-Vladicescu, 2013).
(ix) Heterogeneity. Fog nodes are highly dynamic and heterogeneous to support low latency and application requirements (Hong, Lillethun, Ramachandran, Ottenwälder, & Koldehofe, 2013).
(x) Dynamic optimization per user. As opposed to the cloud which is separated by WANs, a Fog server has the advantage of knowing the network conditions locally for the end user as it belongs to the same network as the end users. Thus, the Fog server can have knowledge of each user which can help choose the best parameters and customize the optimization (Zhu et al., 2013).

When designing this Fog computing proposal for banks we took the following aspects into account:

(i) Closer customer service. Customer support services and datacenters must move from the Cloud to environments that are located closer to the customer (to the Fog layer) so that the user experience is enhanced through adaptive interfaces based on the customization of services increased with context attributes.
(ii) Aspects of security and transparency. They are crucial in this sector for validating transaction identities, fraud alerts, personalized customer service, intruder detection (Otoum, Kantarci, & Mouftah, 2017a; 2017b), etc.
(iii) Need for process agility. Payments, fees, application for credits, currency exchange, crypto currencies, etc.
(iv) Reduction of the banking entity's cost management costs. The implementation of secure services through which the client can contract financial products without customer attention.

1.2. Main contributions of the proposal

Taking into account the characteristics of Fog computing, we propose a novel solution that integrates predictive systems in the process of personalized customer services delivery for the recommendation of the products of a banking entity. We have designed a flexible, efficient, secure and customizable architecture called FOBA (Fog Oriented Banking Architecture), based on Fog computing for the collection and analysis of the data harvested by mobile devices, applications and the local equipment of the bank. The compilation and treatment of all this data is performed through Fog nodes that incorporate light Intelligent Agents for data processing in real time with characteristics of the environment. The key points of the contribution of this work can be summarized in:

- The proposed architecture includes fog nodes where data is processed by intelligent agents.
- It includes a recommender solution for a banking entity that integrates predictive systems.
- To recommend financial products a hybrid recommendation method is proposed.
- The Fog layer will improve the customization of banking products by personal agents.

The motivation behind this research is to improve aspects of customer support services, especially, achieve greater security, increased transparency and agility of processes as well as reduce entity management costs.

The article is structured as follows: in Section 2 we review the existing Fog computing solutions, in Section 3 we present our architecture proposal and contemplate the use of Fog computing use in a bank, also we present the data obtained in relation to the recommendation of banking products. In Section 4 we finish the article with the conclusions and the future lines of work that would improve the suggested Fog computing ecosystem, aimed at banking entities.

2. Review of fog system solutions

We review different Fog computing solutions developed for specific application fields. The main axes of development in fog computing applications correspond to the sanitary field and Smart Cities as well as several other fields of application. This section complies and studies the solutions found in various articles, describing their scope, the approach they follow and their main contribution.

2.1. Fog computing solutions for healthcare applications

The use of IoT devices for the continuous monitoring of the vital signs of patients makes it necessary for health applications to send information in real-time. However, due to their latency sensitivity, Fog architectures have become the preferable architectures for the development of these applications. The articles we have found within this category range from home care applications for the elderly, such as that proposed by Al-khafajiy et al. (2019b), where wearables are used to track an elder person's physiological data to aid in Early Intervention Practices, or the one proposed by Stantchev, Barnawi, Ghulam, Schubert, and Tamm (2015) in which the final IoT/user layer is made up of sanitary sensors. In the latter, the Fog layer consists of gateways that act as Fog nodes and are in charge of short-term storage (reporting to the patient on their current glucose level) and the Cloud layer deploys the components that provide continuous access and evaluate the data of the applications designed to support people affected by chronic obstructive pulmonary disease.

The architecture proposed by Fratu, Pena, Craciunescu, and Halunga (2015) is also designed to reduce latency. In particular it is based on the framework proposed by Kyriazakos et al. (2016) in which an ambient intelligent is proposed for home care in through its sensorization (eWall). The architecture designed by the authors is divided as follows: the IoT/end user layer is composed of different sensors deployed in the user's home (temperature sensors, motion detectors), the Fog layer is responsible of processing data in real time and handling emergency cases through application components deployed in this layer, it also includes architectural modules responsible for monitoring patient movements and additional storage modules. The Cloud layer is responsible for long-term data storage, so caregivers can access the patient's history for a long time. The Cloud layer also includes several modules such as Cloud Middleware and SLA Management.

Another relevant framework is the one developed by (), which serves to create resource preservation networks to assist Emergency Departments. Perfomance indicators were optimized was optimized by means of modeling and simulation to improve the service flow.

An increasing amount of architectures are designated for specific diseases such as Parkinson's disease. Monteiro, Dubey, Mahler, Yang, and Mankodiya (2016) analyze clinical speech data from patients with this disease. The IoT/end user layer contains the device that collects the data, in this case a Smartwatch Android is in charge of collecting the clinical data of the patient's speech. The Fog layer includes the applications in charge of compiling and analysing the information collected by the Smartwatch. The Cloud layer ensures the long-term storage of information, providing access to the person in charge of monitoring the patient's progress. (Al Ridhawi, Mostafa, Kotb, Aloqaily, & Abualhaol, 2017) a caching and data selection strategy is proposed using a framework of cooperation between several agents. Once simulated it shows the reduced latency of data recovery that allows the use of 5G Internet. In addition, the results show a higher success rate in the files, which reduces the number of repeated downloads. In this article we have only reviewed some of the Fog computing architectures applied in the field of patient health and wellbeing, but as shown in Al-Khafajiy, Webster, Baker, and Waraich (2018); Dighriri, Lee, and Baker (2018); Mouradian et al. (2017) there is an increase in the number of architectures aimed at this field. Fog computing allows to customize the application better for its implementation since it is able to filter, process and analyze the information collected by specific devices globally way and in real time, something that is very useful in the case of health applications.

2.2. Fog computing solutions in the field of smart cities

Sensors are deployed in households not only for healthcare-related purposes but also to achieve greater energy efficiency. There have been countless proposals that use sensors data to encourage more energy efficient behavior in users. Smart grids are one of the fields to which Fog Computing has much to contribute. In this section we will review the architectures we have found in this field. Yan and Su (2016) proposed an architecture to improve the data storage and processing of existing smart meters. The final IoT/user layer in this case is the smart home, the building, etc. The Fog layer is made up of smart meters that act as Fog nodes. They act as a specific data node that is considered a master node which includes modules that store the metadata of the file name and storage location. They also include modules that duplicate and divide the collected data and then distribute it to the data nodes at fixed time intervals. The Cloud layer is responsible for backing up data received from Fog nodes.

In the area of Smart Cities we have also found work aimed at the general management of the city itself, Tang et al. (2015) propose a hierarchically distributed four-layer architecture applied to Smart Cities. Layer 4 corresponds to the final IoT/user layer and is the layer containing the sensor network and the sensor nodes. Layers 3 and 2 correspond to the Fog layer. Layer 3 is made up of high-performance, low-consumption edge nodes. Each Edge node is responsible for a local group of sensors. This layer includes components that carry out the analysis of obtained data. Layer 2 is made up of calculation nodes, each of which is connected to a group of Edge nodes in layer 3. This layer includes components that respond quickly to control the infrastructure when dangerous events are detected. The information extracted from these two layers is transmitted to the Cloud layer, to which the authors attribute level 1 and which includes components responsible for very high latency tasks such as the detection and prediction of natural disasters.

Brzoza-Woch, Konieczny, Nawrocki, Szydlo, and Zielinski (2016) proposed a three-layer architecture for advanced telemetry systems capable of supporting an automated flood risk assessment system. The IoT/end user layer is the layer in charge of taking measurements in which sensors are included. In the Fog layer, the authors propose an ecosystem of distributed telemetry stations and components responsible for collecting, processing and sending data from the IoT/end user layer to the central system. The Cloud layer is the one that includes the communication level between the distributed telemetry stations and the central part of the system.

Aloqaily, Al Ridhawi, Salameh, and Jararweh (2019) demonstrate how to replicate data and service composition that are considered promising solutions for managing data and services in densely populated environments. Specifically, they describe how to replicate data from the cloud to the edge, and then to mobile devices to provide quicker access to data for users. In addition, the authors discuss how services can be composed in crowded environments using specific service overlays.

2.3. Fog computing solutions in the commercial field

In addition to the applications we have reviewed in the previous sections, Fog computing is becoming a prominent paradigm in the solutions proposed for large commercial companies. Apart from the academic scope, it is also possible to find commercial IoT platforms of large companies such as Huawei. We have reviewed the following solutions:

(i) Hilink. Huawei introduced the Hilink platform in 2015. It integrates mobile solutions and products designed to address the technological needs of consumers. The platform connects intelligent products such as remotely controlled infrared lights, storage solutions, air quality monitors or intelligent electrical sockets and fans, among many others.

Table 1
State of the art summary.

Solutions	Contributions	Conclusions
Healthcare Al-khafajiy et al. (2019b); Al Ridhawi et al. (2017); Fratu et al. (2015); Kyriazakos et al. (2016); Monteiro et al. (2016); Oueida, Kotb, Aloqaily, Jararweh, and Baker (2018); Stantchev et al. (2015)	Permanent monitoring Latency sensitive	Long term storage Better customization
	Real-time notifications	Data filtering and real time processing
Smart Cities Aloqaily et al. (2019); Brzoza-Woch et al. (2016); Tang et al. (2015); Yan and Su (2016)	More efficient energy use City management	Better storage behaviour Infrastructure control
Companies	Risk assessment Connecting multiple products IoT and Edge computing packages	Automated systems support Data solutions, smart plugs Sensors and custom software, Large-scale management and monitoring software

(ii) IoT and Edge computing packages. The Dell company together with Intel presented in August 2018 new solutions to the implementation of secure and scalable solutions for cases of use of IoT and Edge computing. In this case, Intel has contributed its vision and computer analysis technologies to the proposal. The packages include sensors and licensed software customized for specific customer use cases, along with various combinations of Dell infrastructure (edge gateways, PC hardware, integrated servers, etc.). Software that facilitates large-scale management and monitoring is also included.

Having reviewed a range of solutions that can be developed with Fog computing, in Table 1 we present a summary and the conclusions drawn from the review.

3. Customization of products for financial systems

Today's highly competitive banking, driven in part by the rapid growth of new computing paradigms, together with Financial Technology (Fintech) is pushing the industry to look for ways to continue improving customer relationships. Analytical processes in Cloud environments can leverage large volumes of data to perform computational processing including machine learning techniques to improve reliability, automated configuration, and performance (Mendhurwar & Mishra, 2018).

In the field of e-business, one way of achieving this is through personalized product recommendations. Banks participate in content customization methods in order to expand and align themselves with new digital business mechanisms. In digital businesses, recommendation systems provide users with intelligent product search mechanisms that are adapted to their preferences. The increase in the sale of this type of systems is a consequence of their ability to interact with users to help them choose and discover products and services that are of interest to them. In this sense, the recommendation systems are designed to adapt to each user, becoming a kind of personalized assistant that facilitates access to the many product offers in a more efficient way.

The principal recommendation methodologies (Ricci, Rokach, & Shapira, 2015) are classified into two categories, collaborative and content-based filtering methods. In collaborative filtering methods (Schafer, Frankowski, Herlocker, & Sen, 2007), the recommendations are made by predicting the degree of interest of the active user in relation to certain items. These predictions are based on the group of users that are similar to the active user. In this process some correlation coefficient is used, which expresses the degree of similarity between two users. Collaborative filtering methods can in turn be classified into two types: memory-based and model-based. This classification is performed according to the predictions about the interest in the items of the active user. In memory-based methods predictions are conceived using all the valuations available in the system, while in model-based methods part of them are used to construct a valuation estimation model.

The main advantage of memory-based methods is the rapid incorporation of recent information, however, a serious problem, inherent to these methods, is the lack of sufficient valuations to make predictions. In addition, the scalability can be jeopardized due to the volume of data that must be processed every time a recommendation has to be made to a user. For this reason, model-based methods propose the construction of a model for estimating valuations based on part of the appraisals of the system's items. These methods based on models are also known as methods "based on items", because, as opposed to the methods based on memory, they consider the similarity between the item and those that the user have already rated and/or consumed, to predict user interest in the item. Once the data relative to the similarity of the items in a system is available, a model for estimating valuations is created which can also consider user attributes. This model is created off-line, which means that it is created before the active user enters the system. Therefore, a user behavior model is performed with stored data from the system and in off-line mode. This model is then applied to predict a user's preferences when using the system. Machine learning techniques are commonly used for this (Sohail, Siddiqui, & Ali, 2017).

The main advantage of collaborative model-based filtering methods is the simplicity and speed with which recommendations are made. Most data processing is done off-line, so the time spent building the model has no impact on response time. Nevertheless, their disadvantage is that new information is not immediately incorporated into the model, except when a new model is generated with new information already included in it. Therefore, these methods are indicated for systems in which user preferences change slowly in relation to the time needed to build the model.

Content-based filtering makes predictions by comparing the information that can be extracted from a resource with information that describes users' interests, preferences and habits. The use of these techniques makes it possible to avoid the problem of a shortage of explicit assessments on the part of users. The information that can be extracted, for example, from a resource focused on financial products, is the set of singular characteristics that define them. Currently, there are numerous proposals in the literature based on hybrid approaches, which combine collaborative filtering methods with content-based techniques. The summary of the main recommendation methodologies is presented in Table 2.

4. Proposed architecture

Fig. 1 summarizes the FOBA architecture, key technologies, challenges, and open issues of this proposal. The Fog layer comprises

Table 2
Recommendation methodologies.

Methodologies	Classification	Conclusions
Collaborative filtering Mendhurwar and Mishra (2018); Schafer et al. (2007); Sohail et al. (2017)	Memory-based	1. Fast incorporation of recent information 2. Lack of availability of valuations to predict 3. Scalability is compromised
	Model-based	1. Ease-of-use and faster recommendations of customization 2. Only when a new model is generated the data is incorporated 3. Suitable for systems where users' preferences change slowly to the time needed to build the model
Content-based methods (Mendhurwar & Mishra, 2018)	Hybrid approaches	1. Make predictions by comparing information that can be extracted from a resource with information that describes users' interest, preferences and habits

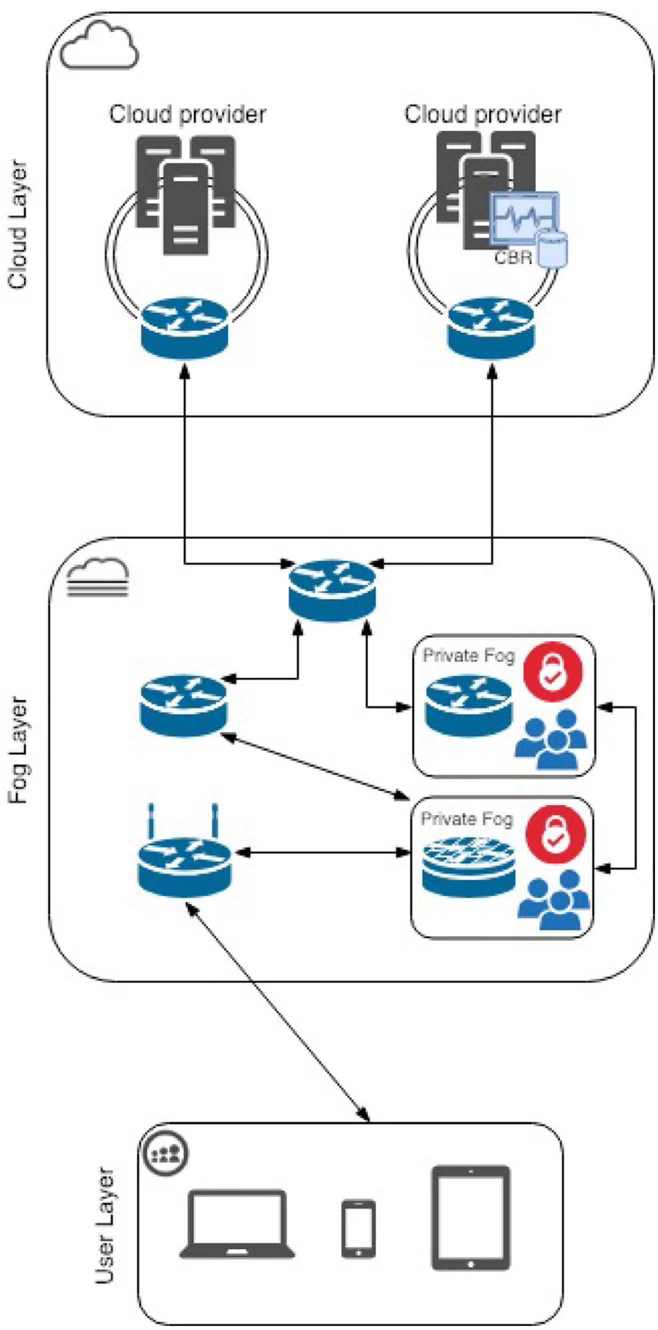

Fig. 1. Architecture diagram.

Table 3
Glossary of abbreviations and acronyms.

WAN	Wide Area Network
FOBA	Fog Oriented Banking Architecture
IoT	Internet of Things
SLA	Service-Level Agreement
IS	Intelligent system
RS	Recommendation system
CBR	Case Based Reasoning
CF	Collaborative Filtering
k-NN	*k*-nearest neighbors
VSM	Vector Space Model
ETF	Exchange-Traded Fund

the "fog nodes" that can be created using devices with low computing capacity and network or storage connectivity. These fog nodes are easily deployable and can interact with users at the edge of the network and collect data. The proposal includes fog nodes where data can be processed with light intelligent agents that allow contextual recommendation systems (Sassi, Mellouli, & Yahia, 2017) to be implemented. These nodes collaborate with users at the edge to achieve certain management tasks, as well as communication storage.

In that fog layer, an Intelligent System (IS) is proposed to execute recommendation system (RS) and machine learning algorithms. IS helps filter banking products among the large volume of available products. This recommendation engine analyzes the information acquired through the sensors along with the information available in the bank to provide suggestions to the user through a personal agent or API that uses collaborative filtering methods. We propose the verification of the recommendation success rates for the storage/deletion of Case Based Reasoning (CBR) cases in the Cloud. This proposal facilitates the sharing, through CBR in the Cloud, of all business intelligence in customer service by the entity. It also allows to establish, at the same time, recommendations through context data in the Fog nodes of the physical branch office.

4.1. Proposed recommendation system for commercial banking

To recommend financial products, such as mortgages, loans, retirement plans, etc., a hybrid method of recommendation is proposed: collaborative filtering (CF) combined with content-based filtering. This is possible by adding attributes of both products and users in order to obtain resemblances. This methodology has been used successfully in other fields of consumption of streaming products (Sánchez-Moreno, González, Vicente, Batista, & García, 2016; Sánchez-Moreno, González, Vicente, Batista, & Moreno-García, 2017).

User based Collaborative filtering collects the ratings of the active user in the domain and matches it with other users in the same domain to generate useful personalized recommendations for the active user (Resnick, Iacovou, Suchak, Bergstrom, & Riedl, 1994). Similarity between users is computed using the user-to-user correlation. This technique finds a set between two users, the active user and the neighboring user, and can be calculated using Pearson's correlation coefficient. The Eq. (1) expresses how to calculate the similarity between two users, where v_{aj} expresses an assessment made by the active user a on a product j, v_{ij} the one made by the user u_i, $\bar{v}_i$ the average of the ratings of the user u_i and $\bar{v}_a$ the average of the valuations of the active user.

$$\mathrm{Sim}(u_a, u_i) = \frac{\sum_j \left(v_{aj} - \bar{v}_a\right)\left(v_{ij} - \bar{v}_i\right)}{\sqrt{\sum_j \left(v_{aj} - \bar{v}_a\right)^2 \left(v_{ij} - \bar{v}_i\right)^2}} \tag{1}$$

Once the similarity coefficients have been calculated, the algorithm gets a list of the K users most similar to the active user u_a. It is said that two users are neighbours whether they provide similar ratings to common consumed financial products.

Now we can then obtain matches between any financial products and users, the basic similarity metric of the cosine distance measure can be used. The algorithm k-nearest neighbors (k-NN) is also commonly used. The aim is to find the k user (neighbors) with the highest coefficient of resemblance to the active user (using both explicit ratings and additional attributes), creating a subset of users for the collaborative filtering application. This prediction is obtained from the weighted sum of the valuations of other users using the following Eq. (2)

$$P(u_a, u_i) = \bar{r}_a + \frac{\sum_{u \in K} (r_{u,i} - \bar{r}_u) \times \mathrm{Sim}(u_a, u_i)}{\sum_{u \in K} \mathrm{Sim}(u_a, u_i)} \tag{2}$$

Then $P(u_a, u_i)$ is the prediction of the valuation that the active user u_a would assign to the item i, where the average rating of the user is $\bar{r}$ and $\mathrm{Sim}(u_a, u_i)$ is the similarity between the active user and the user i, K is the subset of similar k-users, $r_{u,i}$ is the rating of the neighbor u to item i.

The item-based CF approach uses the transposed matrix (items $\times$ users) for predictions. This approach follows Eq. (3), which takes into account the users' valuations of items that are similar to those for which the prediction is going to be made.

$$P(u_a, u_i) = \frac{\sum_{j \in K} (r_{a,j} \times w_{i,j})}{\sum_{j \in K} w_{i,j}} \tag{3}$$

The CBR system often uses the Vector Space Model (VSM) to represent the user profile as well as the item profile in terms of keywords. In VSM each user and each item can be represented in an n-dimensional space where each dimension corresponds to an attribute or keyword. This is the process that will be carried out in the CBR hosted in the Cloud.

4.2. Data obtained from product recommendations

A simplified relational structure which can be used to define a bank database is shown in Fig. 2. Tables are represented by their set of attributes, with the primary keys emphasized and underlined. Foreign keys and their references are represented by arrows in the diagram. The table "Clients" gathers social and demographic information of each of the clients. The balance of their accounts is represented in this simplification by the "Incomes" and "Expenses" tables, which allow to reconstruct the time series with the complete information, from where more refined economic indicators can be retrieved. The products offered by the system are detailed in the "Products" table, while the contracting of products by clients is detailed in the "ProductClient" table.

To provide the recommendations of bank products, multiple sets of instances were generated randomly, using some of the demographic and economic principles described in INE (2017) for different groups of clients, who were assigned various products, following a realistic probability distribution assessed by expert knowledge. The considered products were debit cards, credit cards, current accounts, savings accounts, term deposits, mortgages, loans, and investment products. The latter category aggregates for simplicity assets like stocks, ETFs, warrants, derivatives, investment funds, and pension funds.

To define user affinity, indicators extracted from the database were age, civil status, and economic indicators derived from the Income and Expenses tables. These indicators include the current amount and the recent account balance in time windows of 1, 3, and 12 months. This derived data can be used to provide recommendations to users who are clients of the bank, following Eq. (2). The result is a vector with the estimated probabilities of being interested in each of the products. A single recommendation could be provided by picking the one with maximum weight, or by random sampling according to those. An example of this vector of recommendations is shown in Fig. 3.

Different profiles of users would receive different sets of weights, which reflects how the recommendations were personalized according to the available information of the users. To further understand this behaviour, Fig. 4 shows the distribution of the weight of the recommendation of a certain product (mortgage) for three groups of clients. The horizontal coordinate represents such a weight, so the users that are more likely to get a product are located on the right, while the height of the bar represents the percentage of users in the range of weights in the base of the rectangle. In this example, adults are more likely to be recommended this product rather than students or pensioners. Individuals with higher recommendation weight can also placed on the right of the main peaks: these are the clients with a higher number of attributes in common with others who have a mortgage.

The overall prediction capability of the system can be evaluated using the Spearman's rank correlation coefficient, which compares the product ranking returned by the recommender system with the one used to generate the profile of each individual. The mean value thus obtained was 0.719.

The recommender settings can be modified by varying the notion of similarity which is defined in Eq. (1). Alternative formulations might imply a change in the metric or in the relative weights of the attributes therein —after a standardization preprocessing is performed to allow for their comparison. The optimal definition of the parameters describing the similarity is dataset-dependent, and it is out of the scope of this work.

4.3. Fog system for recommending financial products in a banking institution

In the previous section we have analyzed the FOBA architecture and verified the data that can be obtained by the recommendation system. Now, We begin with the premises and requirements which is the basis of this case of use. Fig. 5 shows a simple view of a bank office. In it we represent the communication channels that the devices will use, all on the same hierarchical level. The area that we address is the identification of the customer's identity by positioning techniques based on sensory networks (Tapia, Fraile, Rodríguez, Alonso, & Corchado, 2013) affecting the different types of actors and/or elements:

(i) Static nodes: fixed elements such as beacons on the ceiling, walls, etc. located e.g. at the entrance to the office or at the cash dispenser.
(ii) Mobile nodes: consist of mobile elements such as mobile phones, cards, wristbands, etc. that will be identified through the customer's banking APIs.

Fog nodes can store lectures from different devices and sensors and can store local information. For example, in our case we consider media content and data related to banking products for their transmission from the fog server to customers, as well as to bank

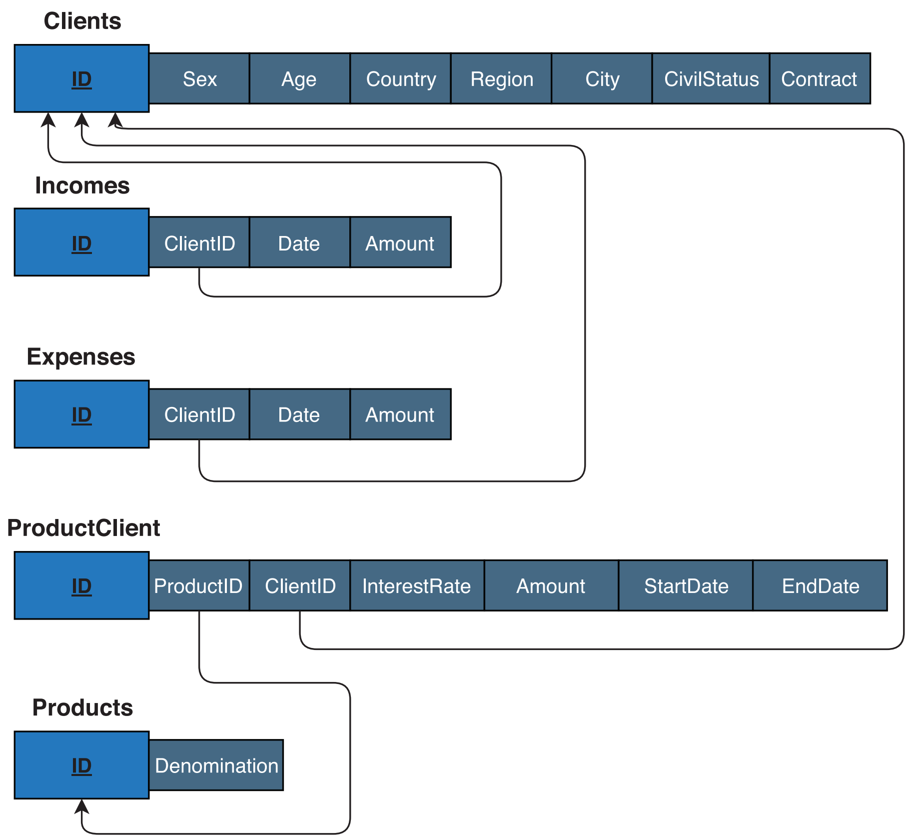

Fig. 2. Relational structure.

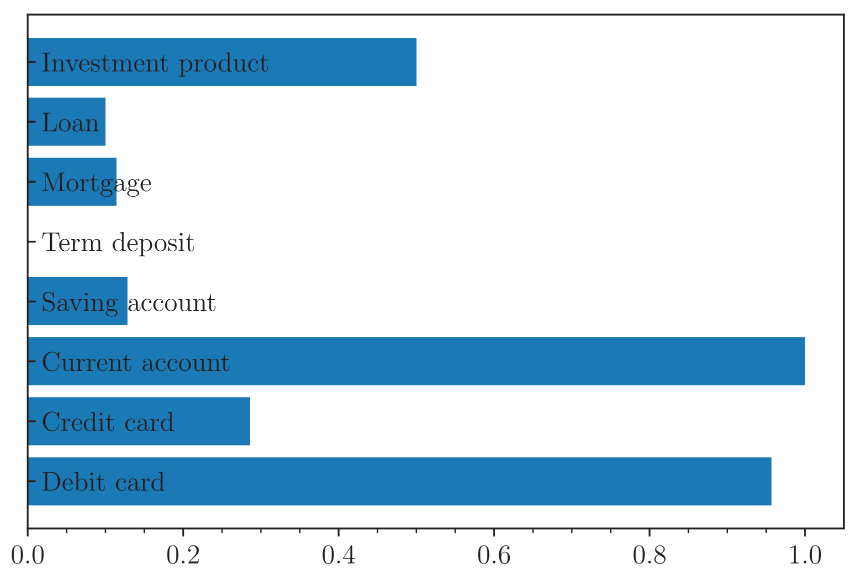

Fig. 3. Example of a vector with the recommendation weights for each of the products for a given user.

operators when active users enter into a bank office. An important aspect that we consider is that once the active user has left the branch, the information collected and analyzed by the system must be available to other bank branches of the same entity, thus generating success cases for the CBR hosted in the Cloud. Customization comprises a series of fundamental and interdependent processes:

(i) Acquisition of user data. The aim is to extend and use the information contained in the log files of the website to improve the data obtained from the user's interaction with the platform.
(ii) Model construction. It is necessary to extend the information and techniques used in the construction of models that support the adaptation tasks performed by the system.
(iii) The identification of adaptive tasks. Related to the built models and the definition of adaptive tasks. It is necessary to identify each cooperative learning task and the type of support needed for its realization.

To achieve a high degree of, the recommendation system must have three main features:

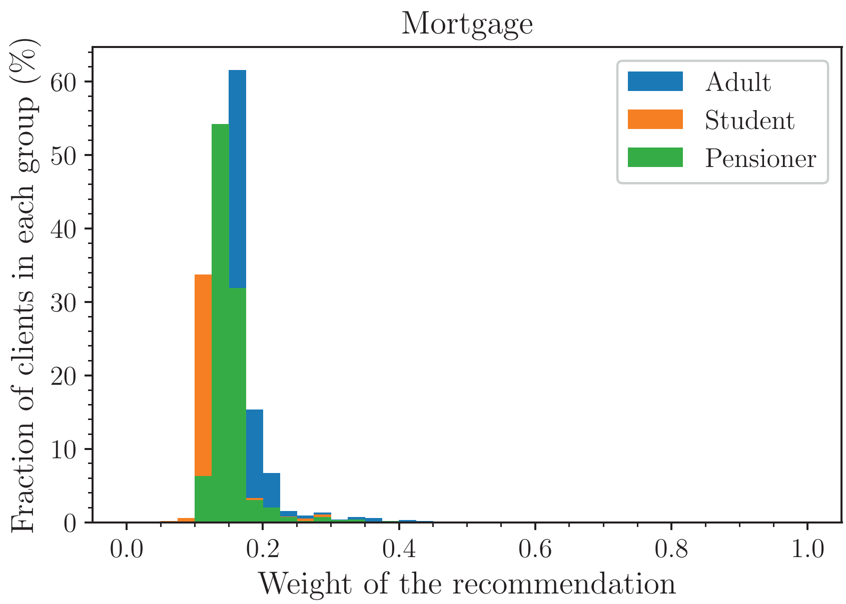

Fig. 4. Distribution of mortgage recommendation weight in different groups.

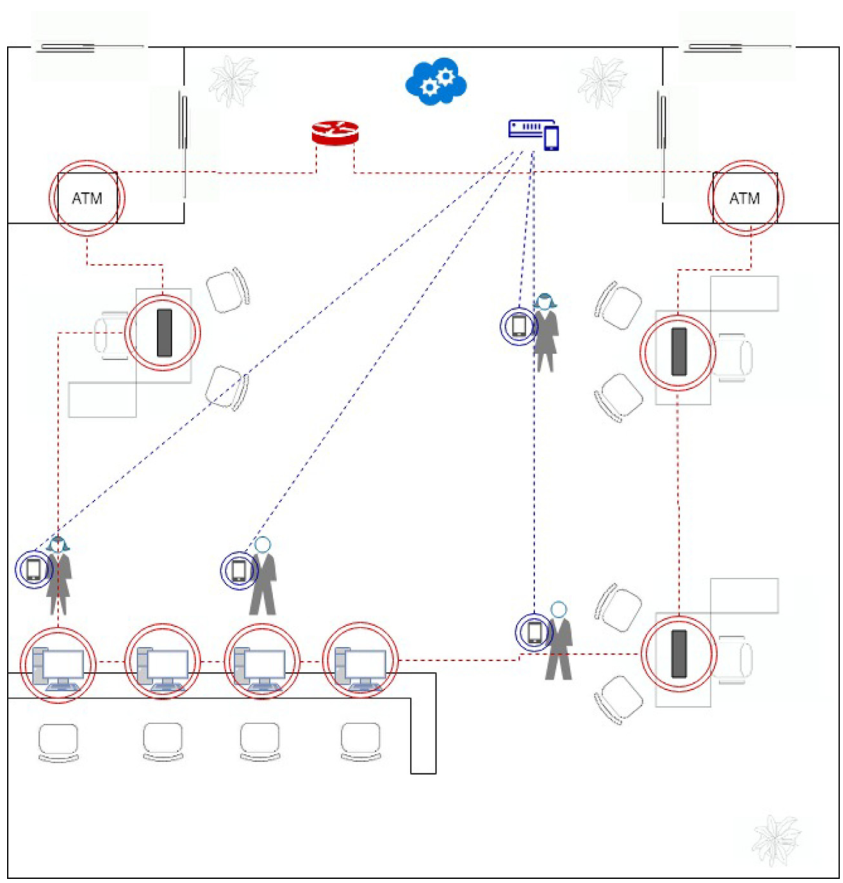

Fig. 5. Fog deployment in a banking institution.

(i) Historical data. Refers to the information available to the system before starting the recommendation process, which comprises user profile data built through user behavior in the system.

(ii) Input data. Refers to data obtained through the interaction (behavior) of users with the system. The recommendations will be made to these users.

(iii) Algorithm. Uses a method based on input techniques and data history to make recommendations.

5. Conclusions and future lines of work

The inclusion of Fog Computing solutions in the scope of device-supported processes is an ever closer reality in all areas. The analysis of the related work has revealed that no significant contributions have been made so far in the area of fog computing frameworks for the banking sector. This fact reveals the need for further research in specific areas of fog frameworks and those linked to the financial sector. In the article we have reviewed the state of the art of Fog computing solutions for several sectors. Based on a similar architecture, we have included a CBR in the Cloud layer, so that through Fog nodes, located in bank offices, light intelligent agents will be integrated to make personalized banking product recommendations. The deployment of the Fog layer will help personal agent customize banking products, and the algorithms to be used in the CBR hosted in the Cloud. A case study has also been proposed to deploy the FOBA architecture.

The proposed architecture offers the opportunity to improve the user experience in the bank's physical channels, so that customers can solve their needs quickly and efficiently and at the same time improve the resolution capacity of the managers in the offices. It also allows for the evolution of the banking service model in offices and for the use of the one-stop shop approach by the processes that support this model, in which managers can solve customer needs through a single point of contact. This architecture allows employees to adopt a more versatile and flexible role, allowing them to address possible customer needs in a comprehensive and personalized manner, improving customer experience and being able to anticipate customer needs. This support therefore allows for a more efficient and personalized use of available commercial bank resources, improving customer service channels.

As a future line of work, we consider the FOBA architecture as a recommendation system based on the environment. It can integrate a recommendation and classification algorithm that ensures the personalization of products suggested by a bank. In this way, the precision of the recommendation of the products is improved through the inclusion of the sentiment analysis of social networks.

Declaration of Competing Interest

The authors declare that they do not have any financial or non-financial conflict of interests.

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References

Al-khafajiy, M., Baker, T., Al-Libawy, H., Maamar, Z., Aloqaily, M., & Jararweh, Y. (2019a). Improving fog computing performance via fog-2-fog collaboration. *Future Generation Computer Systems, 100*, 266–280.

Al-khafajiy, M., Baker, T., Chalmers, C., Asim, M., Kolivand, H., Fahim, M., & Waraich, A. (2019b). Remote health monitoring of elderly through wearable sensors. *Multimedia Tools and Applications*, 1–26.

Al-Khafajiy, M., Webster, L., Baker, T., & Waraich, A. (2018). Towards fog driven IoT healthcare: Challenges and framework of fog computing in healthcare. In *Proceedings of the 2nd international conference on future networks and distributed systems* (p. 9). ACM.

Al Ridhawi, I., Mostafa, N., Kotb, Y., Aloqaily, M., & Abualhaol, I. (2017). Data caching and selection in 5G networks using f2f communication. In *Proceedings of the IEEE 28th annual international symposium on personal, indoor, and mobile radio communications (PIMRC)* (pp. 1–6). IEEE.

Aloqaily, M., Al Ridhawi, I., Salameh, H. B., & Jararweh, Y. (2019). Data and service management in densely crowded environments: Challenges, opportunities, and recent developments. *IEEE Communications Magazine, 57*(4), 81–87.

Bonomi, F., Milito, R., Zhu, J., & Addepalli, S. (2012). Fog computing and its role in the internet of things. In *Proceedings of the first edition of the MCC workshop on mobile cloud computing* (pp. 13–16). ACM.

Brzoza-Woch, R., Konieczny, M., Nawrocki, P., Szydlo, T., & Zielinski, K. (2016). Embedded systems in the application of fog computing-levee monitoring use case. In *Proceedings of the 11th IEEE symposium on industrial embedded systems (SIES)* (pp. 1–6). IEEE.

Dapp, T. (2014). Fintech–The digital (r) evolution in the financial sector. Deutsche Bank Research.

Datta, S. K., Bonnet, C., & Haerri, J. (2015). Fog computing architecture to enable consumer centric internet of things services. In *Proceedings of the international symposium on consumer electronics (ISCE)* (pp. 1–2). IEEE.

Dighriri, M., Lee, G. M., & Baker, T. (2018). Big data environment for smart healthcare applications over 5G mobile network. In *Applications of big data analytics* (pp. 1–29). Springer.

Fratu, O., Pena, C., Craciunescu, R., & Halunga, S. (2015). Fog computing system for monitoring mild dementia and copd patients-romanian case study. In *Proceedings of the 12th international conference on telecommunication in modern satellite, cable and broadcasting services (TELSIKS)* (pp. 123–128). IEEE.

Hajibaba, M., & Gorgin, S. (2014). A review on modern distributed computing paradigms: cloud computing, jungle computing and fog computing. *Journal of Computing and Information Technology, 22*(2), 69–84.

Hong, K., Lillethun, D., Ramachandran, U., Ottenwälder, B., & Koldehofe, B. (2013). Mobile fog: A programming model for large-scale applications on the internet of things. In *Proceedings of the second ACM SIGCOMM workshop on mobile cloud computing* (pp. 15–20). ACM.

INE (2017). *Mujeres y hombres en España*. Catálogo de publicaciones de la Administración General del Estado.

Kyriazakos, S., Mihaylov, M., Anggorojati, B., Mihovska, A., Craciunescu, R., Fratu, O., & Prasad, R. (2016). Ewall: An intelligent caring home environment offering personalized context-aware applications based on advanced sensing. *Wireless Personal Communications, 87*(3), 1093–1111.

Madsen, H., Burtschy, B., Albeanu, G., & Popentiu-Vladicescu, F. (2013). Reliability in the utility computing era: Towards reliable fog computing. In *Proceedings of the 20th international conference on systems, signals and image processing (IWSSIP)* (pp. 43–46). IEEE.

Mendhurwar, S., & Mishra, R. (2018). Emerging synergies between internet of things and social technologies.

Monteiro, A., Dubey, H., Mahler, L., Yang, Q., & Mankodiya, K. (2016). Fit: A fog computing device for speech tele-treatments. In *Proceedings of the IEEE international conference on smart computing (SmartComp)* (pp. 1–3). IEEE.

Mostafa, N., Al Ridhawi, I., & Aloqaily, M. (2018). Fog resource selection using historical executions. In *Proceedings of the third international conference on fog and mobile edge computing (FMEC)* (pp. 272–276). IEEE.

Mouradian, C., Naboulsi, D., Yangui, S., Glitho, R. H., Morrow, M. J., & Polakos, P. A. (2017). A comprehensive survey on fog computing: state-of-the-art and research challenges. *IEEE Communications Surveys & Tutorials, 20*(1), 416–464.

Networking Index, C. V. (2016). Forecast and methodology, 2016–2021, *1*, 0–4.

OpenFog Consortium Architecture Working Group (2017). *OpenFog reference architecture for fog computing*. OpenFog Consortium.

Otoum, S., Kantarci, B., & Mouftah, H. T. (2017a). Detection of known and unknown intrusive sensor behavior in critical applications. *IEEE Sensors Letters, 1*(5), 1–4.

Otoum, S., Kantarci, B., & Mouftah, H. T. (2017b). Mitigating false negative intruder decisions in WSN-based smart grid monitoring. In *Proceedings of the 13th international wireless communications and mobile computing conference (IWCMC)* (pp. 153–158). IEEE.

Oueida, S., Kotb, Y., Aloqaily, M., Jararweh, Y., & Baker, T. (2018). An edge computing based smart healthcare framework for resource management. *Sensors, 18*(12), 4307.

Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., & Riedl, J. (1994). GroupLens: An open architecture for collaborative filtering of netnews. In *Proceedings of the 1994 ACM conference on computer supported cooperative work* (pp. 175–186). ACM.

Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender systems: Introduction and challenges. In *Recommender systems handbook* (pp. 1–34). Springer.

Sánchez-Moreno, D., González, A. B. G., Vicente, M. D. M., Batista, V. F. L., & García, M. N. M. (2016). A collaborative filtering method for music recommendation using playing coefficients for artists and users. *Expert Systems with Applications, 66*, 234–244.

Sánchez-Moreno, D., González, A. B. G., Vicente, M. D. M., Batista, V. L., & Moreno–García, M. N. (2017). Recommendation of songs in music streaming services: Dealing with sparsity and gray sheep problems. In *Proceedings of the international conference on practical applications of agents and multi-agent systems* (pp. 206–213). Springer.

Sassi, I. B., Mellouli, S., & Yahia, S. B. (2017). Context-aware recommender systems in mobile environment: On the road of future research. *Information Systems, 72*, 27–61.

Schafer, J. B., Frankowski, D., Herlocker, J., & Sen, S. (2007). Collaborative filtering recommender systems. In *The adaptive web* (pp. 291–324). Springer.

Sohail, S. S., Siddiqui, J., & Ali, R. (2017). Classifications of recommender systems: A review.. *Journal of Engineering Science & Technology Review, 10*(4).

Stantchev, V., Barnawi, A., Ghulam, S., Schubert, J., & Tamm, G. (2015). Smart items, fog and cloud computing as enablers of servitization in healthcare. *Sensors & Transducers, 185*(2), 121.

Tang, B., Chen, Z., Hefferman, G., Wei, T., He, H., & Yang, Q. (2015). A hierarchical distributed fog computing architecture for big data analysis in smart cities. In *Proceedings of the ASE bigdata & socialinformatics* (p. 28). ACM.

Tapia, D. I., Fraile, J. A., Rodríguez, S., Alonso, R. S., & Corchado, J. M. (2013). Integrating hardware agents into an enhanced multi-agent architecture for ambient intelligence systems. *Information Sciences, 222*, 47–65.

Vaquero, L. M., & Rodero-Merino, L. (2014). Finding your way in the fog: Towards a comprehensive definition of fog computing. *ACM SIGCOMM Computer Communication Review, 44*(5), 27–32.

Yan, Y., & Su, W. (2016). A fog computing solution for advanced metering infrastructure. In *Proceedings of the IEEE/PES transmission and distribution conference and exposition (T&D)* (pp. 1–4). IEEE.

Zhu, J., Chan, D. S., Prabhu, M. S., Natarajan, P., Hu, H., & Bonomi, F. (2013). Improving web sites performance using edge servers in fog computing architecture. In *Proceedings of the IEEE seventh international symposium on service-oriented system engineering* (pp. 320–323). IEEE.