Toward Cloud Computing Transition using Deep Learning Collaborative Recommendation Platform

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Abstract
In an increasingly challenging global environment, companies are forced to reduce their costs to preserve their chances in the competitive markets. In order to become more competitive, companies are looking to reduce management costs starting with the costs of IT infrastructure, which in recent years has become very expensive. Transforming these heavy investment expenses into manageable monthly rental fees is possible via Cloud Computing services. However, the transition process is another issue that should be addressed with extreme care.
This paper aims to propose a framework in collaboration with experts in digital transformation of companies toward Cloud Computing. This framework can be supported by a set of web tools hosted in an online platform and available to users who collaborate to build an entire user experience available for companies that want to migrate to the cloud. Indeed, due to lack of experience in the migration to the cloud, companies are unable to adequately address this phase of digital transition. Besides, since experienced human resources are not often available and expensive, it is interesting to have a scientific and technical framework to assist small and medium-sized enterprises in this transition phase. Using the deep learning techniques, it will be possible to capitalize the experience in a single intelligent repository. This will reduce the cost, as well as, the possibility to build a more reliable and generic knowledge.

Key words:
Deep Learning, Cloud Computing, Collaborative System

1. Introduction

Over the past few years, cloud computing has appeared as a new IT solution for many organisations problems. It offers a variety of services as solutions to users through the Internet. Many types of cloud computing services are nowadays available for organisations, the most common are platform, software application, and infrastructure known as PAAS, SAAS and IAAS [24,25].
Cloud computing is increasingly used in both public and private organisations. In fact, the operating expenses of those organisations is affected by the operational inefficiency of their local data centers. Cloud computing allows organisations to obtain expensive and complex services on demand and following the system called "pays as you go". Thus, more and more organisations are migrating existing applications and infrastructure of business to the cloud.

Despite the large opportunities and benefits offered by the Cloud, new challenges and issues have emerged. Those challenges need to be taken into consideration when moving to the Cloud. It is important to have a methodology that enables organisations to respond effectively to these challenges.
In an organisation, the information system is composed of a set of related entities which are: data, process, hardware, software, and people [21]. Several migration processes have been proposed in the literature [22,23]. However, we have noticed the lack of a process that ensures the migration of information systems by studying and analyzing all its components.
In this paper, we propose a framework that helps in the migration process of an information system into the cloud. The main problem is to select the most adequate cloud provider that matches with the information system requirements. This choice is guided by learning past experiences and gathering experts' instructions.
The remainder of this paper is structured as follows: section 2, presents the background and related works about cloud migration techniques. Then, section 3 goes through artificial intelligence techniques for migration. The next section presents regression techniques in deep learning. In section 5, we present our approach for cloud migration. In section 6, we present the results of our approach. Finally, section 7 concludes the paper and describes our future works.

2. Cloud Migration Solutions

In this section, we focus on the migration work that has been done over the past few years in the field of Cloud migration processes.

2.1 Linear Approaches

J. Bisbal et al. [1], proposed a generic migration process consisting of five different steps: the first step is justification, the second step is the understanding of the legacy system, the third step consists of the development of the target system, the fourth step is testing and the last one is migration. Moreover, a brief overview of the migration

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process and its main activities were introduced. Furthermore, Kh et al. [2] introduced a cloud migration process based on three main activities: (a) understanding of the application architecture, (b) choice of cloud environment type and (c) categorization of the different types of application migration. To move applications to the cloud, three layers are considered: business, application and technical. Additionally, a meta model is proposed to present the architecture of the application and its different layers [2]. The information gathered in the meta model will be the basis for a preliminary feasibility analysis and for choosing the migration strategies to adopt. Similarly, this analysis will allow estimating the migration cost and the risks involved.

A. S. Zalazar et al. [3], presented a workflow based on 13 steps for system migration projects and the deep study of the cloud computing environment. The result is a useful tool that simplifies decision making and business planning for cloud computing migration process. Furthermore, the authors integrate a security plan during the migration process, and finally present some recommendations about Cloud contract to ensure security during the migration process project.

A five-phase approach to cloud migration is proposed in [4], where the main objective is to ensure migration to the cloud and take advantage of its benefits. It is especially available for Amazon Web Services (AWS) cloud. The cloud assessment phase is the first phase in this approach, which allows creating a business case for migrating to the cloud. It consists in identifying costs, examining security and compliance, and determining the gaps between the current architecture and the new architecture adaptable to the cloud environment.

A. Menychtas et al. [5] introduced a new migration methodology called ARTIST and a framework based on the modernization of existing applications to empower the technical and business capabilities. This methodology considers the technical and business aspects of the migration process and has high adaptability to the specific requirements of the application. By using this methodology, developers can take advantage of their software in an efficient way. Therefore, ARTIST seeks to minimize the risks and costs of software modernization and reduce difficulties by adopting cloud computing. The first phase of this methodology is the Pre-Migration Phase which is based on the technical feasibility analysis to get an overview of the design quality of the application and the business feasibility analysis to collect information on the costs and the main risks envisaged.

S. Strauch et al. [7] presented a seven steps methodology that supports applications migration to the cloud environment. The authors define a set of functional and non-functional requirements to support the migration to the cloud and the refactoring of the application. The methodology allows satisfying the identified requirements. The analysis and assessment phases in this methodology include different activities such as: selecting the migration scenario, specifying the functional and non-functional requirements of the source and target data store, selecting the appropriate cloud data store, and identifying conflicts by checking compatibility between the source and target data store.

V. Tran et al. [8] proposed a taxonomy of migration tasks which can be followed by any migration projects. Several activities are proposed in the training and learning category of these tasks such as: the analysis of applications, the identification of their components and the degree of coupling, the identification of the applications components that must be changed, the understanding of the selected Cloud platform, etc. The knowledge and experience of the developers have a significant influence on the efforts spent for training. Also, a migration methodology named Risk Homeostatic Methodology which helps organisations to move their data centers to the cloud is presented in [9]. This methodology is composed of four phases. The assessment phase contains some activities such as: analyze the business, identify key stakeholders in order to define business requirements, assess the cloud readiness and analyze the risks envisaged during migration.

A model-driven process for cloud migration is proposed in [10], where the author uses the service-oriented architecture (SOA) as a reverse engineering strategy of existing information systems. The components of these information systems are modeled, such as data, services, business processes and governance. The created models will form the basis for the construction of the new architecture adaptable to the cloud platform.

2.2 Iterative Approaches

In [6] the author presented a migration strategy (so called SoMLAC) helping organisations to migrate their existing information systems to the cloud. This approach ensures the migration of legacy applications iteratively in three phases identified as Move, Transform and Build. Furthermore, the authors in [11], defined a migration process based on a detailed analysis of the information system and all its components considering all the issues encountered during the migration. Thus, they propose a methodology to assess information systems components in order to help organisations make more adequate decisions. The proposed process is composed of three main iterations: analysis, brokerage and migration. The migration process becomes more critical and complex due to ascendant complexity and size. Automating this process is a promising problem that may face a lot of challenges. Artificial Intelligence may be a key answer to resolve this issue. In the next section we present some Artificial Intelligence techniques adopted for similar migration problems.

3. Artificial Intelligence Techniques for Migration

Jo et al. [12] addressed the case of live migration using a model based on an adaptive machine learning capable of predicting the major characteristics of concerned migration. This issue has been addressed in dependence of the migration algorithm and the workload running in the Virtual Machine (VM). The model was able to predict salient metrics with high performance indicators.

Patel et al. [13] relied on the fact that the available techniques for live migration are not able to predict dirty pages in advance. Thus, they propose a framework based on time series prediction techniques using historical analysis of previous data. The authors proposed two different regression-based models of time series. The first model is based on statistical probability ARIMA (autoregressive integrated moving average) and the second one is developed using statistical learning-based regression model SVR (support vector regression). Based on a real dataset, the ARIMA model can predict dirty pages with 91.74% accuracy and the SVR was able to predict dirty pages with 94.61% accuracy.

Arif et al. [14] proposed a Machine Learning based Downtime Optimization (MLDO) approach which is an adaptive migration approach based on predictive mechanisms that reduce downtime during live migration. The contribution of this work is taking advantage of machine learning methods to reduce downtime. The proposed approach is compared with existing strategies in terms of downtime observed during the migration process and the improvements observed are quite near to 15 %.

Duggan et al. [15] presented a reinforcement learning approach for the selection of virtual machines, that create an efficiency practice for data centers. The dynamic reinforcement learning virtual machine selection policy helps to choose the optimal virtual machine to migrate from one hosting machine to another. The experiment results proved an improvement of the number of migrations when compared to similar approaches. Moreover, Ye et al. [16] considered a Hadoop virtual cluster and its performance have been considered by proposing a dedicated scalable version. The proposed platform presents interesting performance results.

In his work, Moghaddam proposes an approach [17] that is qualified as energy aware. The main idea is based on a minimization virtual algorithm of the Service Level Agreement Violations [6]. By comparing this algorithm to similar approaches, the author illustrated some interesting performance results in terms of energy consumption. In addition to that the authors of [19] have developed a framework for providing recommendations. The recommendation process is based on two important steps using machine learning. The first concerns the adequate representation of the information, while the second step consists of selecting the adequate recommendation that fits with resource constraints.

Mandal et al. [18] proposed to extend a previous model by adding Virtual Machine migration policy from one host to another based on the linear regressor to predict the future resource requests. In his approach, the author aims to predict short-term future resource references. This approach considers existing data about resource consumption and aims to distinguish solicited resources and the available ones. However, this approach does not take into account the minimum request of the demands to ensure a minimum quality of service.

It is important to notice the necessity of service's specification. The aforementioned specification should be a prerequisite before proceeding to migration in order to avoid cloud migration situations where requirements are not satisfied. Moreover, an important problem is to proceed to migration to the most adequate service provider when more than one offer is eligible. It is interesting to use deep learning techniques to learn from previous experiences what fits best for a successful migration. In the next section we present some regression techniques that could be adopted for our solution.

4. About Regression Estimators

Using statistics to solve a problem returns to model the data by a series of observations $x_1, x_2, \dots, x_n$ corresponding to the execution of some random variables $X_1, X_2, \dots, X_n$. The objective is to find a theoretical distribution of the vector$(X_k)_{1 \le k \le n}$ reflecting all or a subset of the properties of the observations $(x_k)_{1 \le k \le n}$.

The estimation techniques are always used when it comes to project and analyse the behaviour of a system. Then it is important to examine the validity of the estimation. Several methods exist for estimating data. We will focus particularly on regression problems. The general purpose of the regression is to best explain a variable y (the variable to explain) as a function of other variables x (vector of regressors).

4.1 Simple Linear Regression

The data are presented by n pairs of observations; they are in the form of Table 1.

Table 1: Simple linear regression: Two variables data presentation

N°	**y**	x_1
1	y_1	x_{11}
2	y_2	x_{12}
3	y_3	x_{13}
...	...	...
...	...	...

...	...	...
n	y_n	x_{1n}

If we consider that the relationship between the two variables y and x_1 is linear, this implies that the variation of one variable is proportional to the other. When taking into consideration that one variable explains the other one, we can write a linear model to explain more their relation: $y_i = \beta_0 + \beta_1 x_{1i} + u_i,\ 1 \leq i \leq n$ with u_i an error term, β_0 and β_1 some constants; and β_1 represents the increase of y depending on the increase of x_1.
When it comes to estimate β_0 and β_1, we generally use the "least squares" method which consists of minimizing the sum of the squares of the error terms:

$$S(\beta_0, \beta_1) = \sum_{i=1}^{n} u_i^2 = \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_{1i})^2$$

4.2 Multiple Linear Regression

This is an extension of the linear regression by p regressors $x_1, x_2, \dots, x_p$ denoted by n observations and y as dependent variable as illustrated in Table 2:

Table 2: Multiple linear regression: data based on p-variable

N°	y	x_1	x_2	...	x_p
1	y_1	x_{11}	x_{21}	...	x_{p1}
2	y_2	x_{12}	x_{22}	...	x_{p2}
3	y_3	x_{13}	x_{23}	...	x_{p3}
n	y_n	x_{1n}	x_{2n}	...	x_{pn}

The following is the regression relation:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_p x_{pi} + u_i,$$
$$1 \leq i \leq n$$

$\beta_0, \beta_1, \dots, \beta_p$ represents the partial regression coefficients of the model. We use the least squares method to minimize the sum of squares of residues as follows:

$$S(\beta_0, \beta_1, \dots, \beta_p) = \sum_{i=1}^{n} u_i^2 = \sum_{i=1}^{n} \left(y_i - \beta_0 - \beta_1 x_{1i} - \beta_2 x_{2i} - \cdots - \beta_p x_{pi}\right)^2$$

4.3 Ridge Regression

Ridge Regression is used for analyzing multiple regression data having strong multicollinearity. The estimation is unbiased with large variance eventually different from exact value. Standard errors are avoided by implementing the bias degree and renouncing the Least Squares method for estimating model parameters.
Ridge regression aims to limit coefficients size in order to gain in terms of prediction error. Thus, the sum of the residual squares is minimized as follows:

$$\hat{\beta}^{ridge} = arg \quad min_{\beta \in R^{p+1}} \{RSS(\beta) + \lambda \quad ||\beta_i||_2^2\}, \qquad RSS(\beta) = ||y - 1_n \beta_0 - X\beta_i||_2^2$$

Theorem: [15] We suppose that X is centered and reduced. The $\hat{\beta}^{ridge}$ solution of the problem is given by:

$$\hat{\beta}^{ridge}{}_i = S_\lambda^{-1} X^T \tilde{y}, \qquad \hat{\beta}^{ridge}{}_0 = \underline{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$$

where $S_\lambda = X^T X + \lambda I_P$ and $\tilde{y} \triangleq y - \underline{y} \ 1_n$.

4.4 Gradient Boosting

This technique [20] is based on decision trees and considered as a weak prediction model. The weights of individuals are corrected according to data values. It optimizes progressively an arbitrary differentiable loss function to seek more accurate prediction.

5. Collaborative Migration Approach

In this paper we propose an approach helping to resolve migration of the information system in a hybrid environment where several cloud providers are offering competitive services and historical data about previous migration experiences are available as well as expert feedback recommendations. We recall that the main goal is to schedule the migration of the information system - considered as a client in our case- into a cloud service provider in an efficient way.

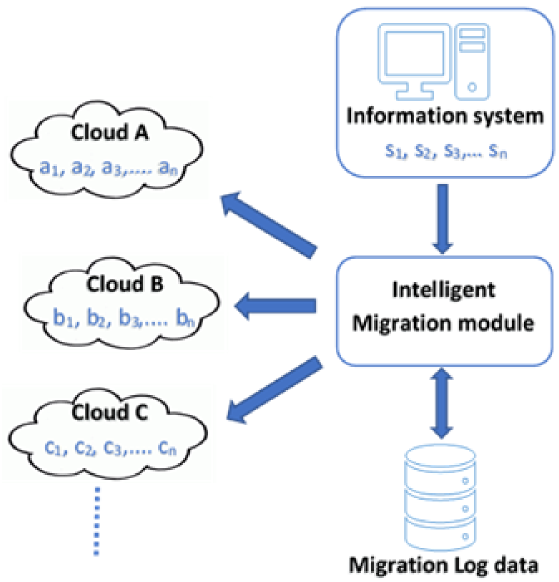

Fig. 1 Intelligent approach for automated migration process

In Figure 1, we illustrate the salient idea of our approach. The role of the migration module is to dispatch the client to the most adequate cloud provider based on the specification of the information system as well as the previous experiences of migration stored in a dedicated data warehouse. The intelligent migration module will attempt to learn from the migration log data to satisfy the current request. Thus, it is interesting to rely on deep learning techniques in order to regress the adequate cloud provider to client requirements.

Furthermore, it is possible to extend this approach as depicted in Figure 2 by interacting with collaborative experts in cloud migration. These experts will analyse the previous migration experiences and supply the migration module with information helping in improving the choice of the cloud provider. The previous information will be in the form of extra variables that will score each cloud service which will be used to seek more accuracy in future predictions.

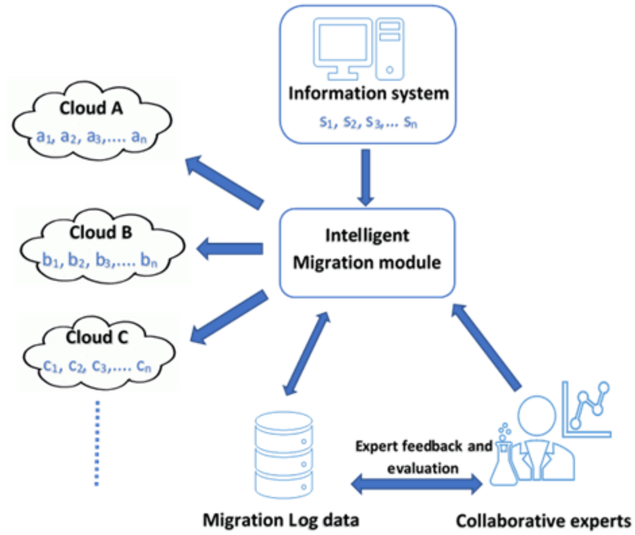

Fig. 2 Collaborative Intelligent approach for automated migration process

6. Results and Discussion

We implemented our approach with python 3.7.3 using spyder 3.3.4 development environment. The regressors models are implemented with *sklearn* library. We used a sample of simulated data (10k observations) about client requirements, 10 cloud provides with 5 different services for each and expert information in the form of non-negative scoring for eligible services. Testing phase used 20% of the aforementioned data and the remaining 80% is dedicated for the learning phase.

In Figure 3, we present a sample of distribution of client requirement and their relation to one of the cloud providers for the same service.

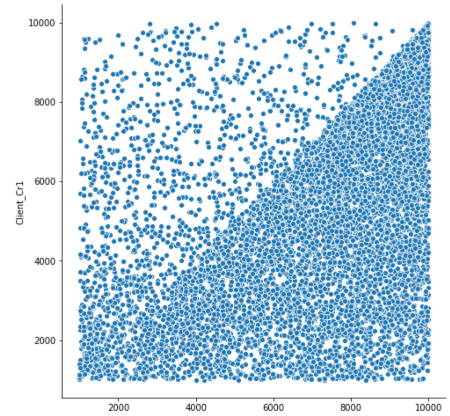

Fig. 3 Distribution of a cloud provider and client requirement about a single service

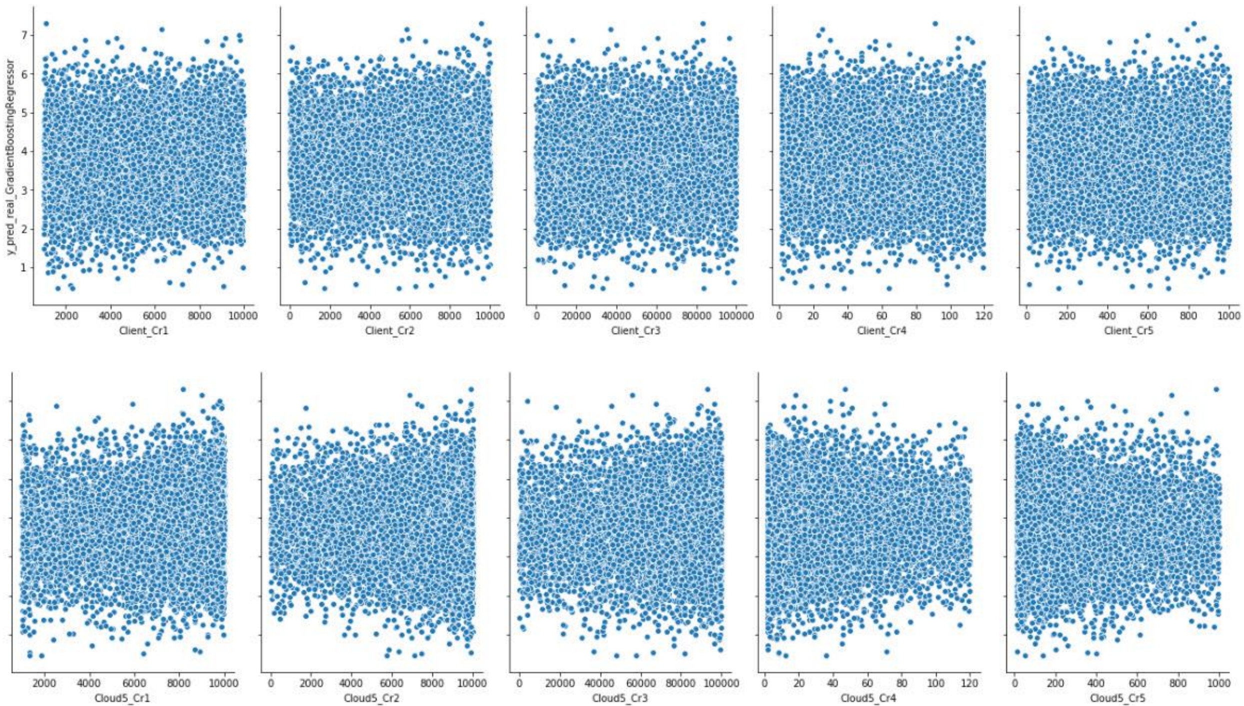

Fig. 4 Gradient boosting regressor output explained by client and cloud data

Figure 4, illustrates the relation between the gradient boosting regressor output and the client data as well as one of the cloud provider information.

The relation between Ridge regression estimation and the first criteria of client requirement and cloud 0 offer is depicted in Figure 5 below.

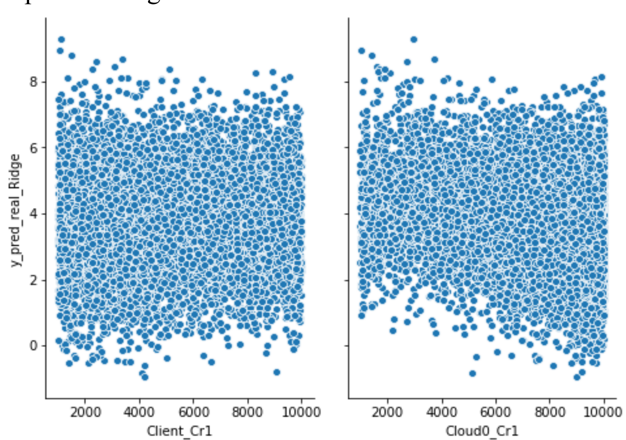

Fig. 5 Relation between Ridge prediction output and one criteria of a cloud provider client requirement

Figure 6, illustrates the linear regression output in relation with some selected input data of client and cloud providers.

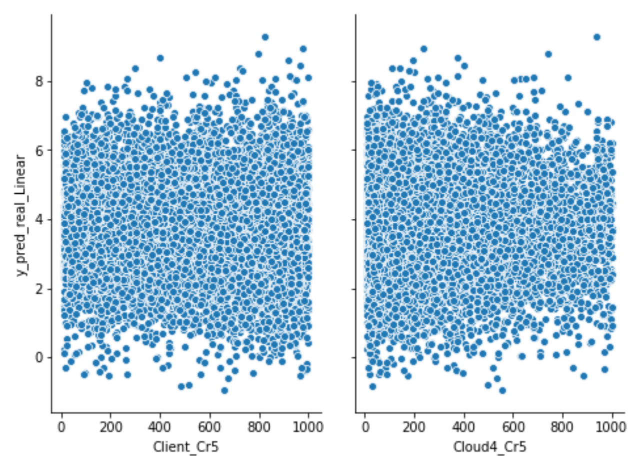

Fig. 6 Relation between Linear regression output and one criteria of a cloud provider client requirement

In all of the previous figures, the scatter plot does not reveal a graphical relation between regressors and the output variable. Mainly, this is due to the complex and hidden relation between a multitude of regressors and the output variable. The output variable cannot be dependent on a single variable when we used more than 50 regressors in our case. However, Gradient boosting, Ridge and linear regressors are able to depict the relation and estimate the output variable.

Table 3: Prediction performance and accuracy

	Without collaborative expert data			Including collaborative expert data		
	Gradient boost regression	**Ridge regression**	**Linear regression**	**Gradient boost regression**	**Ridge regression**	**Linear regression**
Mean Absolute Error (MAE)	2.0878346316	1.9549163267	1.9549163248	1.6221319448	1.8331599933	1.8331585297
Mean squared error (MSE)	5.6825830138	5.3446502596	5.3446502838	4.0942113672	4.9115340606	4.9115536121
ROOT mean squared error (RMSE)	2.3838169002	2.3118499648	2.3118499700	2.0234157673	2.2161981095	2.2162025205
Score	0.2019144204	0.2493751012	0.2493750978	0.4249919370	0.3102037405	0.3102009946

These experiments are performed in two phases. In the first phase input data do not include expert added values, while in the second phase the aforementioned data are included. Table 3 illustrates the performance of these two-prediction tentative with gradient boosting, Ridge and linear regressors. Client requirement data are in the form of scoring associated with each required service. In our case we limited our study to 5 different services for each request. Each cloud provider is supposed to propose an offer to each service with its own score. The expert will evaluate the offer of each cloud and will preselect cloud providers that satisfy all the client requirements. The expert is eligible to decide if the cloud offer is above the minimum request of the client.

The prediction aims to guess the most adequate cloud that fits the most client requirements. In the training phase the regressor is fed with client requirement data. We proceeded in two separate alternatives. The first consists in considering the client requirement and the cloud offers combined with the most suitable cloud defined in the training phase. The second alternative consists in including the experts' collaborative information to the aforementioned data. The expert will include in this case cloud providers that may be selected with an associated score for each of them.

It is important to notice that the prediction with linear regression and Ridge regression are quite similar in our case. However, Gradient Boosting regressor is less efficient when the prediction is based exclusively on client requirement information and cloud services offers, linear and Ridge regression present better accuracy results than Gradient Boosting. Furthermore, Gradient Boosting prediction is enhanced when input data are fed with collaborative expert data. This performance is justified by the hidden relation between the expert estimation in the training phase and the selected cloud to choose which is disclosed by gradient Boosting regressor.

The variable to predict consists of cloud index which should be the most adequate to be selected and meet the information system requirements. We notice that there is no correlation between cloud indexes which make any predicted value different than expected value wrong even if it is an adjacent value.

7. Conclusion

In this paper we focused on the problem of information system migration into cloud computing platform assisted by collaborative expert approach. The main question is to select the most adequate cloud that satisfies all requirements and is elected by the experts. Our resolution approach consists of using deep learning techniques to predict the most adequate cloud to assign to new migration tentative. We illustrated in the previous section that prediction becomes more accurate when the training data is fed with expert recommendation which helps to gain more precision in the prediction process. This aspect is more visible when adopting Gradient boosting regressor for prediction because of its robustness and efficiency in disclosing hidden relations between data variables. The collaboration of experts can be considered in an automatic, semi-automatic or manual way. It helps in prediction accuracy especially when the size of observations and training data is not big enough.

In future works we may focus on other types of data that are qualitative by nature to include. It is also interesting to consider the case where multiple clouds are eligible and have similar scores using multivariable regression techniques.

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