International Journal for Innovative Engineering and Management Research
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IJIEMR Transactions, online available on 4th Aug 2021. Link :http://www.ijiemr.org/downloads.php?vol=Volume-10&issue=ISSUE-08

DOI: 10.48047/IJIEMR/V10/I08/11

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Volume 10, Issue 08, Pages: 65-70

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TRANSFERABLE KNOWLEDGE FOR LOW-COST DECISION MAKING IN CLOUD ENVIRONMENTS

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ABSTRACT :
Users of Infrastructure as a Service (IaaS) are becoming more overwhelmed by the variety of providers and services offered by each. As a result, many consumers choose services only on the basis of their description. A growing option is to utilise a decision support system (DSS), which generally focuses on gathering insights from observational data to help a client in making decisions about optimum cloud application deployment. The core function of such systems is the creation of a prediction model (e.g., through machine learning), which necessitates a massive quantity of training data. This effort, however, is not sustainable due to the varied architectures of apps, cloud providers, and cloud services, since it incurs additional time and expense to collect data to train the models. We address this by developing a Transfer Learning (TL) approach in which knowledge (in the form of a prediction model and associated data set) gained from running an application on a specific IaaS is transferred to significantly reduce the overhead of building new models for the performance of new applications and/or cloud infrastructures. In this work, we demonstrate our method and assess it using extensive testing with three real-world apps running on two large public cloud providers, Amazon and Google. Our study reveals that our unique two-mode TL method improves overall efficiency by reducing the time and expense of developing a new prediction model by a factor of 60 percent. We put this to the test in a variety of cross-application and cross-cloud scenarios.

Keywords : - ***Cloud computing, Decision support, Machine learning, Transfer learning.***

I INTRODUCTION

The cloud computing market is characterised by a plethora of service offerings, price methods, and technological standards [1], [2]. This makes service selection decisions more difficult. Although such problems apply to all tiers of cloud services, the Infrastructure as a Service (IaaS) level is particularly tough since IaaS offers developers with more options and flexibility. There is a large range of virtual machines (VM) available in the IaaS domain – see Figure 1 – but no clear mechanism for comparing their performance and, more broadly, cost/performance trade-offs, neither within nor across cloud providers. A bad or inefficient decision can result in financial

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loss as well as decreased programme performance [3], [4], which is a major worry among end users [5], [6]. The box plots in Figure 2 depict the distributional dispersion of execution times for three different apps across a variety of Amazon EC2 and Google GCE instance types. Throughout.

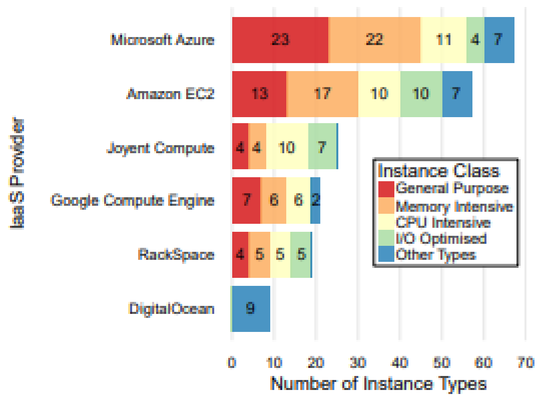

Fig. 1. On-demand instance types (Linux) offered by major IaaS vendors.

II. RELATED WORK

The vast range of technologies, APIs, and terminology used in cloud computing is a significant problem [14]. Furthermore, ambiguity about how these services are handled (e.g., scheduling algorithms, load balancing rules, co-location techniques, and so on) adds a black-box aspect to this complexity. As a result, providing clients with realistic and application-specific deployment options is a critical and difficult aim. Application needs are matched with cloud resources throughout this decision-making process. In general, there are two methods to such a decision-making process, which we will discuss below. Metric-based solutions rely on a certain manner of expressing cloud resources and their capabilities, such as through the use of defined KPIs or benchmarking. Due to the vast breadth and proliferation of the cloud computing industry, the previous technique, despite all attempts, results in an outmoded and reductive depiction. The latter technique avoids this by doing continuous benchmarking in an attempt to detect anomalies and create a thorough and up-to-date performance profile for each cloud resource type. Of course, this comes with a significant operational expense. Furthermore, both techniques have the problem of being dependent on application-agnostic ranking rather than understanding how the application would actually perform on a particular infrastructure. Application models provide a greater emphasis on the other component of the matching choice process: application needs. Vendor-independent ontologies and model-driven engineering are two examples. To gain a comprehensive understanding of business models and corporate strategy, these systems rely significantly on fine-grained information from domain experts, analysts, and decision makers. As a result, while building workflows and architectural models, a designer must consider the influence of decisions, alternative decisions, actor interactions, dependencies, and processes. Such methods need extensive developer knowledge as well as time to adhere to domain-specific design standards.

III PROPOSED SYSTEM

Our objective is to improve the efficiency of intelligent DSSs so that they can make data-driven and application-specific choices in cross-cloud settings (those that span more

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than one provider). We think that efficiency may be accomplished by lowering the training overhead by utilising existing information in the form of experience data sets, relevant predictive characteristics, prediction models, and their parameters. By transferring gained information from a similar domain, we propose a TL-based strategy to assisting in efficient model creation. The suggested technique is intended particularly for IaaS deployment and migration considerations. Our method is a semi-supervised transductive TL methodology that accepts auxiliary target data for model construction. Semi-supervised learning is utilised because of its capacity to learn with a little quantity of labelled data, decreasing the amount of training data necessary for the target domain, which is one of the primary concerns of model generation efficiency. We now discuss our solution's design and implementation (I), as well as the algorithms that underpin the TL scheme (II–III).

IV IMPLEMENTATION

SYSTEM ARCHITECTURE

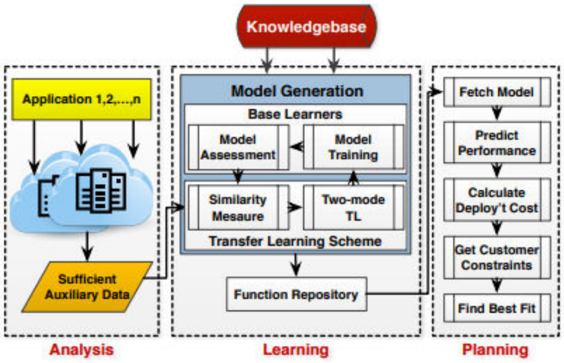

Fig:2. System Architecture.

Figure 4 depicts the major components of the overall system architecture, which include a Knowledgebase and three phases: Analysis, Learning, and Planning. The Knowledgebase contains learning techniques, prediction models, model parameters, and the data sets from which the models are built. The prediction models in the Knowledgebase were created using the conventional ML procedure (train and test with cross-validation) (I.2). Tamakkon's main idea is to efficiently create a prediction model for a specific application, and the 5 process begins with a gathering of auxiliary data (I.3). The Analysis Phase is in charge of supplying supplementary data to the Learning Phase. The auxiliary data is obtained by executing the programme on a representative set of virtual machines and profiling several matrices relevant to the application's deployment and performance. The Learning Phase is the heart of the architecture, and it is made up of four sub-modules, each of which performs a specific task to enable model creation for a certain domain (i.e. application and/or provider). The model, on the other hand, is not built from start by following the lengthy procedures of model fitting, but rather by Tamakkon, which takes use of already obtained knowledge retrieved from the Knowledgebase. The Resemblance Measure identifies the similarity of a new domain (target) to existing ones (source). The auxiliary data is then used by the similarity measure (II) to search the Knowledgebase for a comparable application. Tamakkon transfers existing information using a two-mode TL method based on this similarity, with the objective of improving learning

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efficiency and producing a prediction model for a new application. The 'two mode' portion of the name alludes to the two ways of transferring information between domains: Transfer-All and Transfer-Model. These modes provide several methods for transmitting substantial knowledge, such as instance knowledge, feature space knowledge, and parameter knowledge (III). One of the knowledge transfer mechanisms is engaged in conjunction with the similarity result and a chosen base-learner (I.1). The active mode provides auxiliary and learnt data to the base-learner, which generates a prediction model. Model Training employs training data sets, which can be made up of both source and target domain data depending on the method used. The test data set for model evaluation consists only of data from the target domain. Model evaluation is carried out using 10-fold cross-validation, and if the results are not satisfactory, the procedure is restarted by retrieving the next most comparable application from the Knowledgebase. Finally, the acceptable model is kept in the Function Repository so that the Planning Phase may forecast future application performance. The projected performance results are used to produce deployment costs, which are then utilised to determine the optimum deployment match in line with the customer-specified restrictions. The rest of this section goes through the capabilities of Tamakkon modules, including basic learners, auxiliary data, and similarity assessment.

V CONCLUSION

Due to the broad and ever-expanding range of IaaS service offerings, making decisions in cloud environments is a difficult process. A client joining such a varied market is likely to be perplexed by the variety of options available and lack awareness of the selection criteria. As a result, a decision support system combined with standard machine learning approaches is a highly appealing service for cloud customers. This, however, comes with a substantial learning time and financial cost for making decisions particular to each application and cloud infrastructure. Tamakkon, an unique method for increasing the efficiency of ML-assisted DSS in making application-specific choices in a cross-cloud context, is presented in this work. The solution makes advantage of current knowledge by moving it to new apps and/or cloud infrastructures. This paper, in particular, use TL to determine the type of knowledge to be transferred and describes a system for determining similarity across different sources of knowledge. Tamakkon does not use pre-trained models from the source. Instead, it is training a function on the data from the source and destination applications. This method is assessed from three viewpoints, using two public cloud providers and three apps with different architectures. The assessment findings are highly encouraging, revealing a considerable decrease in model creation overhead (by 60%) in terms of both time and cost. Tamakkon is therefore capable of improving the capabilities of intelligent decision support systems in order to make them more

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cost-effective. This significant contribution is particularly relevant for multi-cloud brokers [13] who must evaluate a wide range of deployment options. This work paves the way for future research in a variety of areas. It would be particularly interesting to augment the framework with extra learning methods, such as the investigation of unsupervised transfer learning approaches. Furthermore, it would be interesting to broaden the study to include multi-criteria decision making and to better understand the generalizability of this method by extending it to other kinds of apps and cloud providers.

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