The Analysis of Time Series Forecasting on Resource Provision of Cloud-based Game Servers

time series forecasting 时间序排预测

resource provision 资源供应

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workload 工作量. elastic 弹性的
on-demand 请求式的.

***Abstract*—The server workloads of large-scale online video games are elastic and on-demand. The workload can range from tens to thousands of server instances in short periods. In fact, a cloud-based video game ecosystem can reach a workload of millions of players every week. Given such a large scale, even a small portion of over-provisioning leads to a significant amount of resource idling and a high cost of waste. It is essential to define an effective forecasting model on the game session workloads given a time span. The effectiveness shall be measured by metrics representing Service Level Objectives (SLOs). In this work, we analyze time series forecasting models using ARIMA, Prophet, and LSTM to predict the number of virtual machines in need of cloud resource monitoring data. In addition, we define service-level metrics for measuring effectiveness based on factors of over/under provision and ratio of resource waste. We analyze models with 16 fleets with an average of 2754 game servers over a four-month-long period of time in the production environment. We observe that our LSTM model is the most accurate in forecasting the demand of virtual machines in terms of RMSE and MAE. Further analysis using metrics of SLOs, we observe that the LSTM model leads to more cases of under-provisioning than ARIMA and Prophet do. The LSTM model forecasts the demand of virtual machines with less over-provision ratio than ARIMA and Prophet do for 14 out of 16 fleets. Using the LSTM model, we further evaluate the forecasting effect across different time spans of a single fleet and across multiple fleets within the same time span.**

目标.

under-provisioning 供应不足 more
over-provisioning 过度供应 less

***Index Terms*—Forecasting Time Series, Resource Provision, Machine Learning, Deep Learning, Service Level Objective**

I. Introduction

Online high-budget video games (known as AAA) are adopting a cloud-based video game ecosystem. Such systems experience workloads up to millions of players in a typical week that demand the game servers of different scales. They can range from tens to thousands of games in short periods. Game servers from cloud providers have two layers of scheduling. The typical life cycle of a game server begins with provisioning a number of virtual machines (VMs) in a fleet. A fleet is a pool of VMs with the same configuration such as capacity, region and operating system. A VM is initialized by starting a given number of identical processes as game servers. A game session is a game in progress with players. Once a game session is created, an available game server process is assigned to handle the game session. Each VM is shared by multiple game servers. When the session ends, the game process is back to an idle state and waits for the next session until the VM is reclaimed.

reclaim 回收的

One of the service-level objectives (SLOs) is to meet the demand for virtual machines and allow players to create new gaming sessions without delay. The number of virtual machines should be in minimal excess to the real demand to reduce the costs of idling virtual machines on the cloud. Hanieh Alipour et al., [1] present a survey that explores the definitions of related concepts of auto-scaling and the taxonomy of auto-scaling techniques. The auto-scaling mechanism ensures the provision of VMs in one of the three kinds, (1) rule-based solutions that specify configurations such as time or a threshold to trigger scaling; (2) reactive solutions that adjust the virtualized resources in response to a changing demand resulting in the changing virtualized resources utilization at the application service level; and (3) proactive solutions that forecast the near future working load at the application service level and adjust the virtualized resources in advance.

excess 超过

proactive 积极主动的

Time series modelling has been applied to implement auto-scaling mechanisms for applications that exhibit a type of temporal pattern. In the case of cloud provisioning, previous works have used time series to predict the number of resources necessary in the future according to different factors [2]–[5]./ Regression-based methods have been applied in cloud resource modelling. Bankole and Ajila in [6] propose a prediction model for VMs needed based on CPU's traces, memory, and network throughput, and SLO metrics, including response time. The authors compare several machine learning techniques, including Support Vector Machine (SVM), Neural Network (NN), and Linear Regression (LR). K-nearest Neighbors (KNN) algorithm-based regression is used in [7] to predict over-utilized and under-utilized Performance Metrics. Calheiros et al. [8] deploy the Autoregressive Integrated Moving Average (ARIMA) model on web requests and network throughput to predict future workloads. Markov chain model is proposed in [9] to autonomously predict and decide the allocation of CPU, Memory and bandwidth on host VMs and thus reduce the cost in cloud services. Hurst exponent, which is widely used in network data flow prediction, is utilized in [10] to measure the predictability of a VM. Filtering and

This paragraph is hard to relate to the previous paragraph

exhibit 表现出

temporal 世俗的,现世的;与时间有关的

赫斯特指数

recurrent 周期性

point out the problems of the above works.

signal processing methods are also used to predict future workloads in VMs. Gong [11] used Fast Fourier Transform (FFT) to detect VMs with a similar pattern in frequency windows. Wu [12] used the Kalman filter to minimize the error of measurement and make the forecasting model robust to the noises and fluctuations. More recently, recurrent neural network models with data correlation analysis have been developed and used to analyze multivariables of cloud metrics [13], [14]. The above work mainly focuses on the workload and resource usage forecasting with less attention on the waste estimation. In the game session context, the forecasting of virtual machine demands should be under the constraints of minimizing both the over-provision and under-provision cases.

analyze three predictive models:
1. LSTM
2. ARIMA
3. Prophet

resilient 有回弹力的；有复原力的

In our work, we define metrics directly related to service level objectives, including (1) the average number of virtual machines wasted during a period of time, (2) under provision ratio, and (3) over provision ratio. These metrics calculated from actual demands and predicted workload are used to evaluate fleets of game servers. We analyze three kinds of predictive models that can predict the number of virtual machines with a minimal excess of real-demands, Long Short Term Memory (LSTM) networks, a traditional forecasting model of ARIMA and an additive model Prophet [15] suitable for strong seasonal effects. The observations help to discover a baseline model for forecasting the future amount of virtual machines while being resilient to unexpected events in an effort to reduce operational costs using cloud resources.

Our forecasting problem becomes forecasting the workload every 10 minutes (10 min is the median time that it takes for a VM to become available) ahead of data of 30 minutes in the past. Therefore, we derive the following context-specific questions in the model analysis:

- **RQ 1:** What are the forecasting effects based on metrics of both the general accuracy measures and service level objectives?
- **RQ 2:** Is a model trained with data from one fleet transferable to forecast to other fleets that are active during the same time period ?
- **RQ 3:** Is a model trained with data from one fleet transferable to other fleets that are active during a different time period?

if the model is transferable to other fleets and different time

The contributions of this paper are three-fold:

1) We define metrics to measure over-provision and under-provision effects of a forecasting model in addition to general accuracy based evaluation;
2) We develop a baseline model using LSTM to analyze the forecasting accuracy across fleets and temporal spans;
3) We analyze the models using data from 16 fleets with an average of 2754 game servers over four months' time in the production environment. Our LSTM model is the most accurate in forecasting the demand of virtual machines in terms of RMSE and MAE. We observe that the LSTM model leads to the least over-provision cases but more under-provisioning cases than ARIMA and Prophet do.

① define metrics to mesure the model's performance and further evaluation
② develop a model using LSTM
③ analyze the model with production data.

II. Related Work

Recent studies have been conducted regarding dynamic cloud resource provisioning. Various approaches and mechanisms for different purposes have been proposed in both academia and industry. They have already been deployed in saving costs in large-scale cloud services. Cloud services require sophisticated resource auto-scaling methods to operate under varying workloads. Auto-scaling approaches aim to acquire and release resources dynamically while maintaining an acceptable quality of service. Rule-based autoscaling is the most popular approach offered by different platforms such as Amazon EC2 or Microsoft Azure. Conditions and rules in those approaches can be defined based on one or more performance metrics such as system level, CPU load, or service level metrics of the average response time or requests in each unit time. The advantage of the rule-based methods is their simplicity, which makes them easy to use in cloud providers. However, the rules are predefined. When the service level objective is sensitive to avoid under-provision or to minimize over-provision, such a rule-based method is not adaptable to the varying demands on resources.

fine-grained 细粒的；详细的；深入的.

Dutreilh et al. [16] investigates horizontal auto-scaling using threshold-based and reinforcement learning techniques. In [17], the authors describe a lightweight approach that operates fine-grained scaling at the virtual machine level scaling in order to improve resource utilization while reducing cloud provider costs. Hasan et al. [18] extend the typical two threshold bound values and add two levels of threshold parameters in making scaling decisions. Chieu et al. [19] propose a simple strategy for dynamic scalability of web services based on the number of active sessions. The strategy scales the number of virtual machines if all instances have active sessions exceeding particular thresholds. Al-Sharif et al. [20] have a rule-based approach where they use Autonomic Computing components that include CPU, memory and bandwidth to improve the system's reliability, availability, and utilization level by scaling resources in response to changes in the cloud system states.

historical data.

Other methods aim to use time series analysis to collect and study the past patterns of historical data to generate a future prediction for the series. Forecasting models such as ARIMA focus on the direct prediction of future values. For example, Morais et al. [3] use time series based approaches to achieve auto-scaling services by proactive and reactive methods. Huang et al. [4] propose a prediction model (for CPU and memory utilization) based on double exponential smoothing to improve the forecasting accuracy for resource provision. Mi et al. [21] use Brown's quadratic exponential smoothing to predict the future application workloads alongside a genetic algorithm to find a near-optimal reconfiguration of virtual machines. Roy et al. [5] present a look-ahead resource allocation algorithm to minimize the resource provisioning costs while

exponential 指数的

guaranteeing the quality of service in the context of auto-scaling elastic clouds.

Regarding machine learning approaches, Bankole and Ajila [6] propose a machine learning model to predict virtual machine resources based on CPU's traces, memory, and network throughputs, and service-level agreement metrics, including response time. Islam et al. [22] predicted resource demand based on neural network and linear regression. Toukir et al. [23] predict workload tendency of a cloud platform based on time-delay neural network and regression methods. Google Autopilot [24] combines time series analysis and reinforce learning algorithms to scale the number of containers and associated CPU/RAM.

The above research works mainly focus on satisfying the demands using rules or accurate prediction. When the service level objectives have constraints on the occurrence of over-provision or under-provision, existing work shall be further extended to represent these constraints. In this paper, we discuss our systematic method of integrating metrics, model development process, and model evaluation to analyze the effectiveness of a forecasting model. An effective forecasting model is essential to automate the autoscaling operations.

III. The Resource Forecasting Method

stateful 有状态的

consist in 在于

spawn 生产

Game servers are stateful, long-lived and have two layers of scheduling.

The first layer is to schedule a VM using a public cloud provider such as AWS, Azure or GCP. The second layer consists in spawning game processes on the provided VM. Each VM can host a various amount of game processes depending on the VM specifications and the game requirements. The game processes are supporting game-sessions that players are creating when they want to play a new round.

A. The Resource Scaling Workflow

mitigate 使缓和

depict 描绘

The cycle of life of game servers is as follows: a virtual machine is requested from the cloud; the virtual machine starts a number of identical processes sharing the state of the virtual machine, and the virtual machine is reclaimed according to a de-provision policy. During this lifecycle, the initialization of a stateful server requires loading the initial state from the data source. Hence, the process of booting and the initialization of the game servers takes a variable amount of time to complete before being ready for handling players' sessions. In addition to that long-lived stateful game servers share their states across servers. Therefore scaling mechanisms for servers running stateless functions are not suitable for stateful game servers. To mitigate the initialization delay, the current solution consists in initializing a given certain number of virtual machines running idle processes. When a new game server process is required, one of the idle processes is selected. Figure 1 depicts the resource planning center that sends scaling orders to a cloud manager in the Infrastructure-as-a-Service layer that distributes the players over the game fleets. Each game fleet is composed of several virtual machines hosting the game servers.

The current planning center uses the rule-based service of AWS *GameLift*. GameLift tracks a fleet's system-level metrics and determines when to add or remove virtual machine instances based on a set of alerts and actions defined. For instance, if there are fewer than ten available game server processes for 5 minutes, then add ten cloud instances. Either the whole number of instances or percentages of the current instances can be used to define the values in a condition or an action. There are two methods of auto-scaling to choose:

- **Target-based scaling** – GameLift scales the fleet up or down as a certain percentage of current idling server processes. Given a fleet with thousands of game servers, a small difference of the percentage (such as one percent) may have large changes of the server amount (such as hundreds of game servers).
- **Rule-based scaling** – More fine-grained control of scaling actions are given. Each policy specifies an alert condition that triggers a scaling action. Servers within a fleet have unbalanced workloads. The control is performed at the fleet level as a cluster but not fine-grained for each virtual machine.

responsive 反应迅速的

incurs 带来；招致；

Too small granularity of value may not be responsive to the fast increasing game server process demands that lead to under-provision and players' unsatisfactory experience. On the other hand, too large granularity incurs extra costs of idling virtual machines. We extend the rule-based planning center to the forecasting of future virtual machine demands 10 minutes ahead. This prediction value is then used by the planning center to configure the scaling policy. In our work, we aim to achieve two goals of forecasting : (1) forecasting accuracy and (2) minimizing over-provision. Any forecasting with a difference to the real demand results in either over-provision or under-provision. The current business goal is to reduce the idling server cost, which means minimizing over-provision cases while always having enough servers to meet the demand.

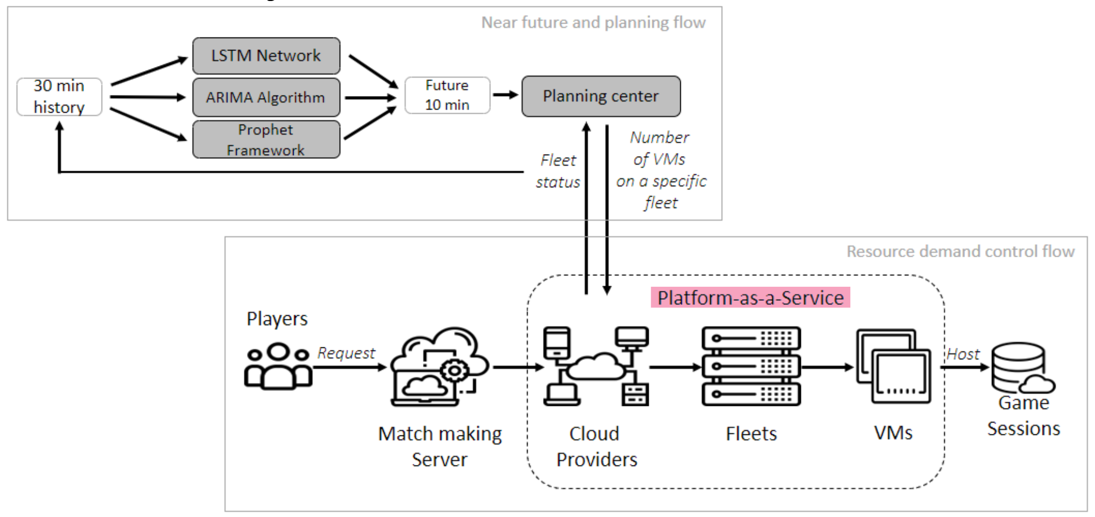
B. The Dataset

The historical data used for forecasting is retrieved from AWS *CloudWatch* logs that contain run-time metrics of fleets, including the number of active fleets during their life cycle. Every minute; the duration of activity for each fleet; the number of active virtual machines of each fleet, the total number of active game servers and free game servers. A fleet's lifetime is up to two months. The fleets' life cycle may not overlap on the timeline. The dataset used in this paper consists of 16 fleets in total in two time spans with ten days overlapping. Eight fleets are active from 2019-12-12 to 2020-02-16, and another eight are active from 2020-02-06 to 2020-03-02. Figure 2 plots the statistics.

stationarity 平稳性

First, we test the stationarity of the time series before evaluating the forecasting models. We perform the Augmented Dickey-Fuller test (ADF) [25], a kind of unit root test that determines how strongly a time series is defined by a trend. The null hypothesis of the test is that the time series can be

Fig. 1. The Resource Provision Workflow for Stateful Game Servers



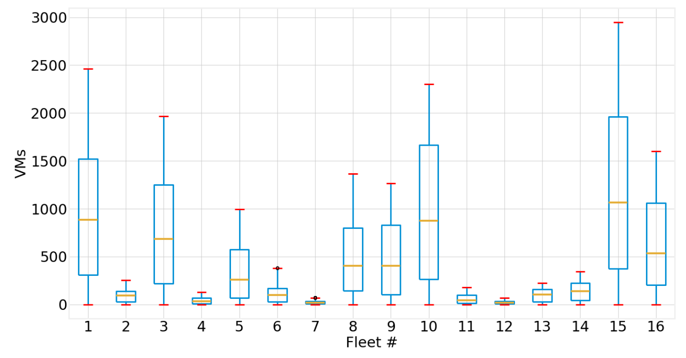


Fig. 2. The aggregation of active numbers of virtual machines on 16 fleets

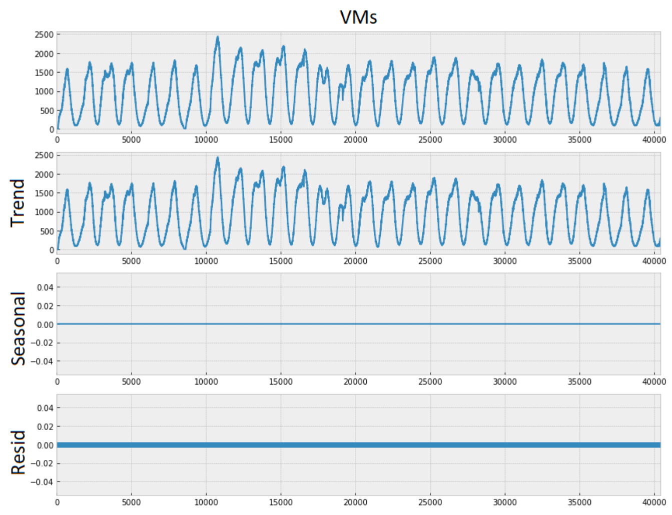


Fig. 3. Seasonal Decomposition of the game sessions of one of the fleets.

decomposition 分解

represented by a unit root, that it is not stationary. The alternative hypothesis is that the time series is stationary. We interpret these results using the p-value from the test. A p-value below the threshold 0.5 suggests we reject the null hypothesis and the time series is stationary. Otherwise, a p-value above the threshold suggests we accept the null hypothesis with a unit root that indicates non-stationary. Figure 3 plots the With the number of active game servers of *Fleet-1*. The ADF test implies that the series of *Fleet-1* is not stationary. Therefore, we consider the forecasting models of ARIMA (autoregressive model), Prophet (an additive model with non-linear trends), and the LSTM recurrent neural network model.

duplicated sentence

C. Metrics for Service Level Objectives

We define metrics for service level objectives to consider the cases of under-provision and over-provision for a forecasting result. The over and under-provisioning cases are denoted O and U, respectively. We define the service level objectives of two kinds. One kind measures the ratio of over-provision and under-provision. The other kind measures the average number of virtual machines wasted. The historical virtual machine demand over a period of 4 months from a rule-based system is used as a benchmark to evaluate any forecasting models.

benchmark 基准

TABLE I
TERMS FOR DEFINING METRICS OF SLOS

→ defined metrics for SLOs

Notation	Description
$\mathbf{O}$	The set of over-provision cases
$\mathbf{U}$	The set of under-provision cases
T	The time span of the time series
N	The number of data samples
pro_t	The number of virtual machines provisioned at time t
dem_t	The number of VMs demanded at time t
Wr_t	The ratio of wasted virtual machine at time t
Mr_t	The mis-forecasting ratio Mr_t at time t
Mr_o	The average over-forecasting ratio across all the time steps
Mr_u	The average under-forecasting ratio across all the time steps

pro_t：在t时，计划中心预测分配的VM数
dem_t：在t时，需要的VM数
Wr_t：——，浪费的VM的比例

At a given time t, the number of wasted virtual machines is defined as $pro_t - dem_t$, the difference between pro_t the number of virtual machines that the resource planning system/framework provides at time t and dem_t the number of virtual machines actually needed to host all the game sessions at time t. Over a time span with N timestamps, the average demand given all the over-provision cases is defined as $\frac{\sum_{t=1}^{N} dem_t}{N}, t \in O$. We then define the ratio of wasted virtual machines at time t as follows:

$$Wr_t = (pro_t - dem_t) \div \frac{\sum_{t=1}^{N} dem_t}{N}, \quad t \in O \qquad (1)$$

precentile 百分位

We compute the percentile of $Wr_t, t \in O$ (1) over the whole time span of the dataset and take the 50_{th}, 90_{th}, 95_{th} and the 99_{th} percentile of Wr as the evaluation metrics.

The number of provisioned virtual machines is also the output from forecasting models. To evaluate the ratio of either under-forecasting or over-forecasting amount compared to forecasting result, we define the metrics of mis-forecasting ratio Mr_t at time t as follows:

mis-forecasting:

$$\frac{\text{预分配VM数} - \text{实际需求VM数}}{\text{预分配VM数}}$$

Pro_t: system/framework 给出的预测值

$$Mr_t = \frac{pro_t - dem_t}{pro_t} \qquad (2)$$

when $Mr_t > 0$, the ratio represents over-forecasting at time t and when $Mr_t < 0$, the ratio indicates under forecasting at time t. We define the average mis-forecasting ratio across all the time steps as follows:

over forecasting

under forecasting

$$Mr_o = \frac{\sum_{t \in O} Mr_t}{|O|}, (Mr_t > 0) \qquad (3)$$

$|O|$

absolute of the data set?

the amount of it?

$$Mr_u = \frac{\sum_{t \in U} Mr_t}{|U|}, (Mr_t < 0) \qquad (4)$$

We define the over-provision ratio (OPR) and under-provision ratio (UPR) to categorize the two cases. We have OPR as the ratio of all the over-provision cases to N; and UPR as the ratio of all the under-provision cases to N.

$$OPR = \frac{\sum_{t=1}^{N} op_t}{N} \times 100\%, \qquad (5)$$

$$UPR = 1 - \frac{\sum_{t=1}^{N} op_t}{N} \times 100\%, \qquad (6)$$

This flag is defined as a Boolean variable at time step t as:

$$op_t = \begin{cases} 0 & pro_t < dem_t \\ 1 & pro_t \geq dem_t \end{cases}, \qquad (7)$$

IV. The Time Series Forecasting Models

A time series consists of three components: the trend, the seasonality and the noise. The trend can be defined as the upward and downward movements of the data over a period of time. Seasonality is the repeating short-term cycle in the series. The noises are the spikes and decreases at random intervals. Our dataset is extracted from the logs of AWS cloudwatch. The intervals are not regular, and the time spans of each fleet are not the same, thus forming an irregular time series. Time series also add the complexity of a sequence dependence among the input variables. We consider the forecasting models of the autoregressive model of ARIMA, an additive model for datasets with trends of Prophet, and a non-linear neural network model of LSTM.

time series { trend / the seasonality / the noise

spike 猛增，急升

time series is irregular

redundant

A. Time Series Modeling in ARIMA

univariate 单变量的

acronym 首字母缩写的 redundant

Our ARIMA model performs univariate time series forecasting by using the previous values of active virtual machines to predict the future values. ARIMA is an acronym that stands for Auto-Regressive Integrated Moving Average. It is a class of models that captures a suite of different standard temporal structures in time series data. ARIMA's parameters are:

- p, the lag order;
- d, the degree of differencing;
- q, the order of moving average.

The fact is that our dataset contains observations taken at different times, which necessitates value analysis of the number of lag observations and specification of the size of the moving windows. In this paper, we set up the ARIMA model using the auto_arima function from the API pmdarima [26]. The auto_arima returns the best ARIMA model according to either AIC (Akaike Information Critera), AICc (Corrected AIC), or BIC (Bayesian Information Criteria) values. The function conducts a search over possible models within the order constraints provided. Using our data, auto.arima returned the parameters, $p = 1$, $d = 1$ and $q = 2$. We fit the ARIMA model with the parameter order (1,1,2).

necessitate 使…成为必要

B. Time Series Modeling in Prophet

Prophet [15] was created by Facebook to capture trends and seasonality in time-series data. Prophet is able to capture daily, weekly and yearly seasonality along with holiday effects by implementing additive regression models. The mathematical model of Prophet is $y(t) = g(t) + s(t) + h(t) + e(t)$. $g(t)$ which represents the linear curve for modelling non-periodic changes in time series. $s(t)$ represents periodic changes in weekly, monthly or yearly). $h(t)$ represents the effects of holidays on irregular schedules. $e(t)$ is the error term accounts for any unusual changes not accommodated by the model. Prophet works best with time series that have strong seasonal effects and several seasons of historical data. By default, the Prophet model automatically computes the parameters according to the data given. A *Prophet()* object is designed to fit on the dataset by calling the *fit()* function and passing the input data. The fit function takes the time series data in a specific format. The first column of data contains the dates and times. The second column contains the sample observations or values. The forecasting is made by calling the *predict()* function by passing the dates and times for all the intervals that we aim to predict.

C. Long Short-Term Memory

We define an LSTM model of two layers. The first layer has a 100-dimensional hidden state followed by 200 hidden units for the second layer. These two layers are followed by a fully-connected layer to output the prediction of active virtual machines in the next 10 minutes. This 10-minute interval is

100-d hidden state

200-d hidden units

fully-connected layer

set for the delay of the virtual machine to start and receive new players. The model's input data has the shape [samples, timesteps]. We transform our dataset into $X = x^1, x^2, ..., x^n$, where x^t is a vector of active virtual machines of the 30 previous time steps as shown in Figure 5.

To train the LSTM model, the data is split in a particular way to prepare the historical and future data. As shown in Figure 4, we divide the data into multiple input/output segments of which the current time step and the previous 29 time steps are used as inputs. Future 10 time steps are used as the output of the LSTM model. We normalize the data in the range [0.01, 0.99] using a Min-Max scaler.

Fig. 4. Method of Splitting the Data for the LSTM model

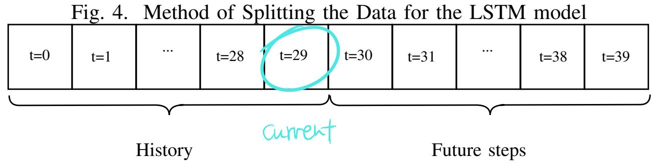
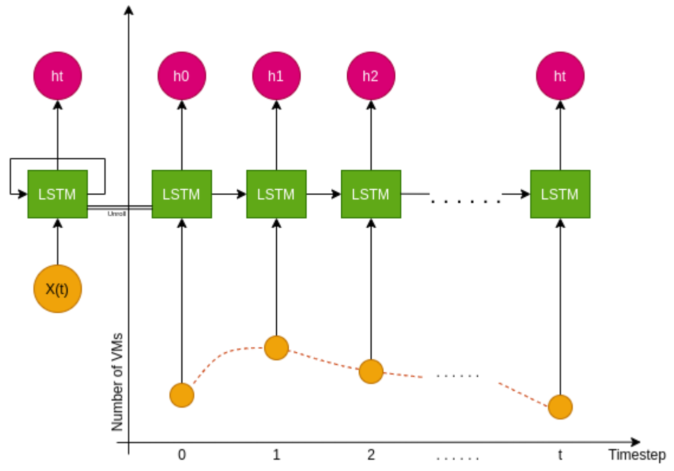


Fig. 5. LSTM uses time series data as input



V. The Model Analysis

In this section, we perform different experiments to answer three research questions.

- RQ 1: What are the forecasting effects based on metrics of both the general accuracy measures and service level objectives?
- RQ 2: Is a model trained with data from one fleet transferable to other fleets that are active during the same time period ?
- RQ 3: Is a model trained with data from one fleet transferable to other fleets that are active during a different time period?

We analyze the models using two sets of metrics: error metrics for measuring the analysis accuracy and the metrics defined in section III-C for measuring effects on service level objectives. Mean Square Error (RMSE) is calculated by taking the average of the square of the difference between the original and predicted values of the data. Mean Absolute Error (MAE) is the average of all absolute errors. The MAE of a model refers to the mean of the absolute values of each prediction error on all values of the test dataset.

① error metrics : accuracy
② SLO effects mesurement .

$$MSE = \frac{\sum_{t=1}^{n}(p_t - x_t)^2}{n} \tag{8}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_t - p_t}{x_t}\right| \tag{9}$$

A. Forecasting Effects (RQ.1)

This experiment aims to observe the model's forecasting effects in both model accuracy and how they perform on over-provision and under-provision cases. We use the current rule-based active virtual machines as the baseline to compare the effects of forecasting models. Table II lists the RMSE and MAE for rule-based baseline and three forecasting models across 16 fleets. Each fleet is trained with one forecasting model, and such a model is applied to predict the virtual machine demand for the next 10 minutes. The experiment results show that the LSTM model produces the least errors for 15 fleets out of 16 fleets.

use the current rule-based active virtual machines

We further observe the effects of over-provision and under-provision. Table III lists each model's two metrics OPR and UPR across 16 fleets. The results show that the LSTM model outperforms other forecasting models with the least over-provision ratio. Compared to the rule-based model, the ratio is reduced up to 90%. For the ratio of under-provision, the LSTM model is not the optimal model. The Prophet model has the least under-provision ratio for 8 fleets out of 16 fleets, and the ARIMA model obtains the least under-provision ratio for 5 out of 16 fleets. The LSTM model has higher under-provision ratios than the other two models. In terms of the number of virtual machines under-provisioned in ratio to the amount predicted by the model, Table IV shows the LSTM model has comparable ratios with the other two forecasting models. In the case of over-provision, the LSTM has better results than the other two models. This indicates the metric UPR only measures the number of cases that are under-provisioned. When considering the metric of Mr_u that measures the differences of quantity in mis-forecasting, we can observe that LSTM has the best forecasting errors with the lowest over-provision occurrence and quantity over time. The quantity of virtual machines under-provisioned is comparable to the other two models.

over-provisioning ratio
under-provisioning ratio

the number of virtual machines under-provisioned in ratio to the amount predicted by the model.
供应不足的VM数和model预测数量的比例.

We further observe the number of over-provisioned virtual machines over time. This effect is measured by the ratio of wasted virtual machine Wr_t at each time step. Table V lists the 50th, 90th, 95th and 99th percentiles of each forecasting model. Across 16 fleets, the LSTM model demonstrates the least ratio of virtual machines over-provisioning over time

TABLE II
FORECASTING ERRORS FOR RULE-BASED AND THREE MODELS ACROSS 16 FLEETS

Fleet NO.	$RMSE_{Rule-based}$	$RMSE_{LSTM}$	$RMSE_{ARIMA}$	$RMSE_{Prophet}$	$MAE_{Rule-based}$	MAE_{LSTM}	MAE_{ARIMA}	$MAE_{Prophet}$
0	322.58	**93.62**	1221.39	328.28	290.86	**66.01**	1221.39	284.28
1	101.1	**7.57**	82.66	30.04	90.64	**7.57**	82.66	25.16
2	**90.66**	124.12	1028.68	253.97	261.10	**124.12**	1028.68	212.89
3	56.08	**5.10**	44.35	24.01	51.66	**5.10**	44.35	20.66
4	201.52	**42.75**	688.31	131.31	173.94	**42.75**	688.31	112.91
5	105.92	**11.22**	109.22	23.28	94.23	**11.22**	109.22	16.59
6	38.58	**3.82**	15.77	7.12	37.74	**3.82**	15.77	5.43
7	223.23	**46.34**	603.58	555.78	206.49	**46.00**	603.58	494.45
8	228.88	**30.11**	436.10	149.97	197.77	**30.11**	436.10	111.51
9	340.87	**58.01**	757.06	314.64	289.68	**58.01**	757.06	248.20
10	74.50	**6.29**	43.61	12.65	64.41	**6.29**	43.61	10.15
11	40.64	**4.16**	17.134	8.72	38.95	**4.16**	17.13	6.87
12	105.49	**6.95**	60.83	22.90	94.35	**6.95**	60.83	19.13
13	114.06	**11.73**	90.97	52.94	103.29	**11.73**	90.97	43.71
14	361.17	**59.86**	670.44	508.44	316.93	**59.86**	670.44	457.67
15	242.68	**39.72**	384.08	277.55	230.41	**39.72**	384.08	251.39

ratio of all the under/over provision cases to N

TABLE III
MODEL FORECASTING EFFECTS ON OVER-PROVISION AND UNDER-PROVISION ACROSS 16 FLEETS BY OVER/UNDER PROVISION RATIOS

Fleet NO.	$OPR_{Rule-based}$	OPR_{LSTM}	OPR_{ARIMA}	$OPR_{Prophet}$	UPR_{LSTM}	UPR_{ARIMA}	$UPR_{Prophet}$
0	31%	5.7%	**1.3%**	40%	75%	99%	**25.4%**
1	54.8%	**4.7%**	40.3%	35.6%	77%	84%	**13.9%**
2	33.9%	**27%**	56.39%	40%	56%	**0%**	23%
3	61.7%	**18%**	63.3%	51.06%	44%	21.26%	**19.9%**
4	42%	**5.2%**	65.97%	48.1%	83%	**0.05%**	29.1%
5	51.7%	**20%**	54.3%	26%	37%	**10.97%**	31.4%
6	69.9%	**25%**	58.11%	33.9%	45%	**23.72%**	26.4%
7	36.6%	6.3%	**2.8%**	55.4%	43%	99.99%	**5.1%**
8	40%	**9.8%**	61.83%	14.26%	39%	**17.60%**	71.15%
9	31%	**3.5%**	61.57%	30.3%	72%	28.41%	**15.7%**
10	59.4%	**6.9%**	52.62%	18.61%	**64%**	73.94%	66%
11	65.5%	**16.3%**	52.32%	32.7%	45.3%	22.75%	**20.19%**
12	55.7%	**5.1%**	64.49%	30.8%	62.5%	56.62%	**12.36%**
13	48%	**5.3%**	56.6%	31.6%	58%	30.38%	**8.05%**
14	28%	**10.4%**	58.9%	37.3%	59.5%	58.52%	**0%**
15	34.9%	**6.47%**	46.72%	37.5%	71.4%	66%	**0%**

average mis-forecasting ratio across all the time.

TABLE IV
THE RATIO OF OVER/UNDER PROVISION AMOUNT COMPARED TO THE FORECASTING AMOUNT

Fleet NO.	Mr_o				Mr_u		
	RB	L	A	P	L	A	P
1	0.32	0.06	0.01	0.40	-0.08	-18.38	-0.11
2	0.55	0.05	0.40	0.36	-0.95	-7.46	-0.06
3	0.34	0.27	0.56	0.40	-0.11	-0.01	-0.08
4	0.62	0.18	0.63	0.51	-0.10	-0.17	-0.11
5	0.42	0.05	0.66	0.48	-0.24	-0.01	-0.17
6	0.52	0.20	0.54	0.26	-0.06	-0.10	-0.11
7	0.70	0.25	0.58	0.34	-0.17	-0.28	-0.47
8	0.37	0.06	0.03	0.55	-0.23	-6.74	-0.10
9	0.40	0.10	0.62	0.14	-0.15	-0.08	-2.15
10	0.31	0.04	0.62	0.30	-1.65	-0.10	-1.48
11	0.59	0.07	0.53	0.19	-3.00	-4.73	-1.15
12	0.66	0.17	0.52	0.33	-0.31	-0.21	-0.20
13	0.56	0.05	0.64	0.31	-1.13	-0.82	-0.05
14	0.48	0.05	0.57	0.32	-0.20	-0.22	-1.04
15	0.29	0.10	0.59	0.37	-0.05	-0.96	0.00
16	0.35	0.06	0.47	0.38	-0.07	-1.73	-0.27

steps. This indicates the LSTM has stable forecasting overtime for 30 minutes of historical data in learning and 10 minutes of data forecasting.

Summary. To answer the first research question, we observe the experiment results by viewing metrics for both accuracy and service level objectives. Our metrics provide indicators to observe the occurrence and quantity of over/under-provision. The LSTM model produces stable forecasting performance across fleets and over time. Thus, the LSTM model is further evaluated for the transferability of the model trained on one fleet and one-time span to other fleets and other time spans.

B. *Forecasting on different fleets (RQ2.)*

In this experiment, we aim to observe the transferability of learning from one fleet to others that are active during the same time span. Such a learning is useful for a new fleet being added to service where no previous observations can be used to predict the future ones. Thus we experiment by using data from some fleets that are active during the same time span to predict the future values of other fleets. We use fleet 0 to train an LSTM model and predict the future values of 7 other fleets active during the same time period. We observe the prediction effect of over-provision and under-provision of each fleet. Table VI lists the two metrics OPR and UPR across 7 fleets. The observation shows that the LSTM outperforms the rule-based model with the least over-provisioning. Compared to the rule-based model, the over-provisioning ratio drops to 6% in some cases. However, the LSTM model still has high under-provisioning ratios.

applicable to new flees

ratio of wasted VM $\longrightarrow$

TABLE V
PERCENTILE OF THE RATIO OF WASTED VIRTUAL MACHINES ALL THE TIME FOR RULE-BASED AND THREE FORECASTING MODELS ACROSS 16 FLEETS

Fleet NO.	Wr(50%)				Wr(90%)				Wr(95%)				Wr(99%)			
Model	RB	L	A	P	RB	L	A	P	RB	L	A	P	RB	L	A	P
0	0.27	0.01	0	0.33	0.58	0.03	0	0.55	0.69	0.04	0	0.60	0.79	0.07	0	0.70
1	0.89	0.03	0.05	0.27	1.51	0.08	0.11	0.53	1.55	0.10	0.12	0.59	1.63	0.15	0.14	0.70
2	0.32	0.01	1.44	0.31	0.62	0.03	2.16	0.49	0.72	0.04	2.18	0.52	0.85	0.09	2.20	0.59
3	0.97	0.04	1.32	0.49	1.73	0.12	1.77	0.88	1.84	0.16	1.81	0.94	3.21	0.24	1.84	1.04
4	0.44	0.02	2.29	0.32	0.79	0.05	2.89	0.54	0.82	0.06	2.91	0.63	0.90	0.11	2.92	0.76
5	1.04	0.03	1.13	0.13	1.24	0.08	1.79	0.26	1.28	0.11	1.81	0.29	1.38	0.19	1.84	0.46
6	1.92	0.09	1.07	0.25	2.29	0.28	1.50	0.62	2.39	0.36	1.56	0.76	2.75	0.55	1.61	1.05
7	0.45	0.01	0.02	0.98	0.57	0.04	0.02	1.69	0.63	0.05	0.02	1.81	0.75	0.08	0.02	1.91
8	0.55	0.02	1.43	0.11	0.69	0.05	1.95	0.37	0.73	0.07	1.97	1.21	1.75	0.28	1.99	1.89
9	0.28	0.03	1.18	0.28	0.50	0.08	1.59	0.56	0.59	0.10	1.61	0.63	0.67	0.14	1.63	0.75
10	0.86	0.09	0.11	0.11	1.48	0.23	0.19	0.34	1.59	0.27	0.21	0.46	2.84	0.37	0.23	0.59
11	1.56	0.10	0.86	0.29	1.89	0.29	1.43	0.55	2.59	0.35	1.47	0.61	3.37	0.52	1.56	1.09
12	1.26	0.05	0.62	0.19	1.47	0.13	0.79	0.38	1.52	0.15	0.81	0.45	1.63	0.20	0.85	0.58
13	0.93	0.05	0.93	0.35	1.09	0.13	1.35	0.55	1.12	0.15	1.37	0.64	1.50	0.23	1.40	0.82
14	0.25	0.03	0.53	0.41	0.49	0.05	0.67	0.68	0.56	0.05	0.68	0.79	0.65	0.07	0.77	1.00
15	0.42	0.01	0.27	0.42	0.51	0.04	0.38	0.69	0.55	0.05	0.39	0.79	0.71	0.08	0.51	0.95

TABLE VI
PREDICTING ON MULTIPLE FLEETS OF THE SAME TIME SPAN (2019-12-12 TO 2020-02-06). FLEET 0 IS USED TO TRAIN THE MODEL AND THEN PREDICT FLEET 1 TO 7. FOR THE RULE-BASED IS ALWAYS OVER-PROVISIONED SO THAT THE UNDER-PROVISIONING IS ALWAYS 0.

Fleet NO.	$OPR_{Rule-based}$	OPR_{LSTM}	UPR_{LSTM}
1	54.8%	12%	68.9%
2	33.9%	6.1%	74%
3	61.7%	16%	63%
4	42%	11%	66%
5	51.7%	10%	66%
6	69.9%	20%	55%
7	36.6%	5.9%	77%

C. Forecasting on different time spans (RQ3)

In this experiment, we aim to observe the model's forecasting effect by training and testing using fleets active during different time periods. We train our model using fleet 0 and test on 8 other fleets active during a time period different than the time of fleet 0. Table VII shows the OPR and UPR results obtained from the prediction of the 8 fleets. The results show that the LSTM outperforms the rule-based model with the least over-provisioning ratio. However, the under-provisioning ratio is still high compared to the rule-based system that is always zero.

TABLE VII
PREDICTION RESULTS FROM TRAINING AND TESTING FLEETS THAT ARE ACTIVE ON A DIFFERENT PERIOD. FLEET 0 ACTIVE DURING THE PERIOD (2019-12-12 TO 2020-02-06) IS USED TO TRAIN THE MODELS AND THE FLEETS 8 TO 15 ACTIVE DURING THE TIME PERIOD (2020-02-06 TO 2020-03-02) ARE USED FOR PREDICTION

Fleet NO.	$OPR_{Rule-based}$	OPR_{LSTM}	UPR_{LSTM}
8	40%	12%	66%
9	31%	6.5%	76%
10	59.4%	16%	61.4%
11	65.5%	19%	59%
12	55.7%	14%	71%
13	48%	9.4%	72%
14	28%	6.3%	74.8%
15	34.9%	6.4%	76%

Summary The results of the experiments show that it is possible to predict the future values of the fleet using a different fleet from a different time period. It shows that the LSTM is able to learn and transfer the behaviour of the fleets between time periods. We evaluate the transferability cross time spans of the LSTM by training with a fleet from one period and testing with seven fleets from a different period. The LSTM model predicts the future values with over-provision ratio lower than the rule-based system.

Our validation has internal threats as cross-validation with every fleet to predict all other fleets should be carried out for observing the transferability. Further analysis on the data at different time spans should be carried out to observe the data trends and seasonablity and their effects on the transferability.

VI. CONCLUSION AND FUTURE WORK

This paper presents the analysis for forecasting models of stateful server resource demand on cloud. To observe the effects of forecasting models, we define additional metrics that measure both the occurrence and quantity of over-provision and under-provision over time. These metrics when combined with general accuracy metrics of RMSE and MAE, produce the level of explainability to the forecasting effects and thus provide better decision making during the automated resource planning process. We analyze the models using data from 16 fleets with an average of 2754 game servers over four months' time spans in the production environment. Our LSTM model is the most accurate in forecasting the demand of virtual machines in terms of RMSE and MAE. We observe that the LSTM model leads to the least over-provision cases but more under-provisioning cases than ARIMA and Prophet do. From the observation, we establish a base model of LSTM and train the model with one fleet data to predict other fleets under the same time span and under different time span. Both cases have reduced over-provision ratio in quantity and in occurrence.

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References

[1] H. Alipour, Y. Liu, and A. Hamou-Lhadj, "Analyzing auto-scaling issues in cloud environments," in *Proceedings of 24th Annual International Conference on Computer Science and Software Engineering*, ser. CASCON '14. USA: IBM Corp., 2014, p. 75–89.

[2] V. R. Messias, J. C. Estrella, R. Ehlers, M. J. Santana, R. C. Santana, and S. Reiff-Marganiec, "Combining time series prediction models using genetic algorithm to autoscaling web applications hosted in the cloud infrastructure," *Neural Computing and Applications*, vol. 27, no. 8, pp. 2383–2406, 2016.

[3] F. J. A. Morais, F. V. Brasileiro, R. V. Lopes, R. A. Santos, W. Satterfield, and L. Rosa, "Autoflex: Service agnostic auto-scaling framework for iaas deployment models," in *2013 13th IEEE/ACM International Symposium on Cluster, Cloud, and Grid Computing*, 2013, pp. 42–49.

[4] J. Huang, C. Li, and J. Yu, "Resource prediction based on double exponential smoothing in cloud computing," in *2012 2nd International Conference on Consumer Electronics, Communications and Networks (CECNet)*. IEEE, 2012, pp. 2056–2060.

[5] N. Roy, A. Dubey, and A. Gokhale, "Efficient autoscaling in the cloud using predictive models for workload forecasting," in *2011 IEEE 4th International Conference on Cloud Computing*. IEEE, 2011, pp. 500–507.

[6] A. A. Bankole and S. A. Ajila, "Predicting cloud resource provisioning using machine learning techniques," in *2013 26th IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*, 2013, pp. 1–4.

[7] F. Farahnakian, P. Liljeberg, and J. Plosila, "Lircup: Linear regression based cpu usage prediction algorithm for live migration of virtual machines in data centers," 09 2013, pp. 358–364.

[8] R. Calheiros, E. Masoumi, R. Ranjan, and R. Buyya, "Workload prediction using arima model and its impact on cloud applications' qos," *IEEE Transactions on Cloud Computing*, vol. 3, pp. 1–1, 08 2014.

[9] C. Jiang, L. Duan, C. Liu, J. Wan, and L. Zhou, "Vraa: Virtualized resource auction and allocation based on incentive and penalty," *Cluster Computing*, vol. 16, 12 2013.

[10] C.-T. Lu, C.-W. Chang, and J.-S. Li, "Vm scaling based on hurst exponent and markov transition with empirical cloud data," *Journal of Systems and Software*, vol. 99, 01 2014.

[11] Z. Gong, X. Gu, and J. Wilkes, "Press: Predictive elastic resource scaling for cloud systems," 11 2010, pp. 9 – 16.

[12] Y. Wu, Y. Yuan, G. Yang, and W. Zheng, "Load prediction using hybrid model for computational grid," in *2007 8th IEEE/ACM International Conference on Grid Computing*, 2007, pp. 235–242.

[13] M. Balaji, A. K. Cherukuri, and G. Rao, "Non-linear analysis of bursty workloads using dual metrics for better cloud resource management," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, pp. 1–16, 12 2019.

[14] N. Tran, T. Nguyen, B. Nguyen, and G. T. Nguyen, "A multivariate fuzzy time series resource forecast model for clouds using lstm and data correlation analysis," in *KES*, 2018.

[15] S. Taylor and B. Letham, "Forecasting at scale," *The American Statistician*, vol. 72, 09 2017.

[16] X. Dutreilh, A. Moreau, J. Malenfant, N. Rivierre, and I. Truck, "From data center resource allocation to control theory and back," in *2010 IEEE 3rd international conference on cloud computing*. IEEE, 2010, pp. 410–417.

[17] R. Han, L. Guo, M. M. Ghanem, and Y. Guo, "Lightweight resource scaling for cloud applications," in *2012 12th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (ccgrid 2012)*. IEEE, 2012, pp. 644–651.

[18] M. Z. Hasan, E. Magana, A. Clemm, L. Tucker, and S. L. D. Gudreddi, "Integrated and autonomic cloud resource scaling," in *2012 IEEE network operations and management symposium*. IEEE, 2012, pp. 1327–1334.

[19] T. C. Chieu, A. Mohindra, A. A. Karve, and A. Segal, "Dynamic scaling of web applications in a virtualized cloud computing environment," in *2009 IEEE International Conference on e-Business Engineering*. IEEE, 2009, pp. 281–286.

[20] Z. A. Al-Sharif, Y. Jararweh, A. Al-Dahoud, and L. M. Alawneh, "Accrs: autonomic based cloud computing resource scaling," *Cluster Computing*, vol. 20, no. 3, pp. 2479–2488, 2017.

[21] H. Mi, H. Wang, G. Yin, Y. Zhou, D. Shi, and L. Yuan, "Online self-reconfiguration with performance guarantee for energy-efficient large-scale cloud computing data centers," in *2010 IEEE International Conference on Services Computing*. IEEE, 2010, pp. 514–521.

[22] S. Islam, J. Keung, K. Lee, and A. Liu, "Empirical prediction models for adaptive resource provisioning in the cloud," *Future Generation Computer Systems*, vol. 28, no. 1, pp. 155–162, 2012.

[23] M. T. Imam, S. F. Miskhat, R. M. Rahman, and M. A. Amin, "Neural network and regression based processor load prediction for efficient scaling of grid and cloud resources," in *14th International Conference on Computer and Information Technology (ICCIT 2011)*. IEEE, 2011, pp. 333–338.

[24] K. Rzadca, P. Findeisen, J. Świderski, P. Zych, P. Broniek, J. Kusmierek, P. K. Nowak, B. Strack, P. Witusowski, S. Hand, and J. Wilkes, "Autopilot: Workload autoscaling at google scale," in *Proceedings of the Fifteenth European Conference on Computer Systems*, 2020. [Online]. Available: https://dl.acm.org/doi/10.1145/3342195.3387524

[25] S. J. Leybourne, "Testing for Unit Roots Using Forward and Reverse Dickey-Fuller Regressions," *Oxford Bulletin of Economics and Statistics*, vol. 57, no. 4, pp. 559–571, November 1995.

[26] T. G. Smith *et al.*, "pmdarima: Arima estimators for Python," 2017–, [Online; accessed 18-11-2021]. [Online]. Available: http://www.alkaline-ml.com/pmdarima