

Mini Project Report on

AWS- SPOT INSTANCES PRICE PREDICTOR

Submitted by

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CHEMBUR, MUMBAI - 400088.

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Awarded accreditation for Computer & Information Technology Engineering by NBA
(for 3 years w.e.f. 1st July, 2019)

Certificate

This is to certify that the report of the mini project entitled

AWS- SPOT INSTANCES PRICE PREDICTOR

is a bonafide work of

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submitted to the

UNIVERSITY OF MUMBAI

during semester V

in

COMPUTER ENGINEERING DEPARTMENT

Guide

(Prof. Uday Bhawe)

I/c Head of Department

Approval for Mini Project Report for T. E. Semester V

This mini project report entitled “**AWS- SPOT INSTANCES PRICE PREDICTOR**” by **Chinmay Shinde, Jinesh Chudasama, Umang Bid and Anoushka Dighe** is approved for the partial fulfillment of the requirement for the completion of Semester V.

Name and Sign of Internal Examiner _____

Name and Sign of External Examiner _____

Date:

Place:

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Name of Student	Class	Roll No.	Signature
1. Chinmay Shinde	TE4	50	
2. Jinesh Chudasama	TE4	07	
3. Umang Bid	TE4	04	
4. Anoushka Dighe	TE4	10	

Date:

Attendance Certificate

Date

To,
The Principal
Shah and Anchor Kutchhi
Engineering College, Chembur,
Mumbai-88

Subject: Confirmation of Attendance

Respected Sir,

This is to certify that Third year (TE) students
Chinmay Shinde, Jinesh Chudasama , Umang Bid and Anoushka Dighe

have duly attended the sessions on the day allotted to them during the period from
_____to_____for performing the Mini Project titled **AWS- SPOT INSTANCES**
PRICE PREDICTOR

They were punctual and regular in their attendance. Following is the detailed record of the student's attendance.

Attendance Record:

Date	Student1	Student2	Student3	Student4
	Present/Absent	Present/Absent	Present/Absent	Present/Absent

Signature and Name of Inte

Abstract

By offering scalable and affordable computing resources on demand, cloud computing has completely changed how businesses deploy and manage their applications. A key player in the cloud computing market, Amazon Web Services (AWS) provides a variety of instances, including Spot Instances, which let users bid on available EC2 capacity and save up to 90% on prices. The Spot Instance prices, however, are extremely erratic and subject to quick changes in response to supply and demand.

We give a comparative analysis of machine learning methods for forecasting AWS Spot Instance costs in this paper. For various instance kinds and localities, we gathered past Spot Instance pricing. We compared the efficiency and prediction accuracy of a number of regression models, including gradient boosting, decision trees, random forests, and linear regression.

Our findings demonstrate that machine learning methods are capable of accurately and efficiently forecasting Spot Instance prices. With an average R^2 score of 0.95 and a root mean squared error (RMSE) of 0.002, gradient boosting in particular beat other models in terms of precision and efficacy. The most significant predictors of Spot Instance pricing, according to our analysis of the significance of several factors, were CPU utilization and instance type.

In conclusion, our study shows the potential of machine learning methods for forecasting AWS Spot Instance costs, which can assist users in streamlining their cloud cost and resource allocation strategies.

Acknowledgment:

The success of this project would not have been possible without the constant encouragement, advice and from a vast number of people. Things, they say, often remain unimplemented.

Very few of them, if find support are turned into actual working models.

This idea as well would have remained, but for one person, the real debt of gratitude that we owe to her, without whom this project would not have been possible.

We, the members of team who developed “Amazon spot instances and prediction” would like to express our sincerest regards to our project coordinator "Mrs. Krupa Chotai", "HOD Uday Bhavesh", "Principal Bhavesh Patel" for their valuable inputs, able guidance, encouragement, and constructive criticism throughout the duration of our project.

Furthermore, we would like to thank the entire staff of CM Department for valuable information provided by them in their respective fields and landing us a helping hand when we most needed it.

Great thanks to all our friends for their presence, as it enhanced our motivation by making us feel at home. Finally, I would like to acknowledge the support and the backbone of this project, the team Members who have always pushed us to do better and finally produce our best work.

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1. Introduction

Due to their availability, adaptability, and accessibility, cloud services are growing in popularity as a result of the rising demand for storage and computing resources. This makes them one of the most effective ways to manage the massive amounts of organisational data. One of the most well-liked business strategies in the cloud computing industry is pay as you go. Platform as a Service (PaaS), Software as a Service (SaaS), and Infrastructure as a Service (IaaS) are just a few of the services offered by the cloud. One well-known cloud computing platform, AWS, provides a selection of virtual instances. The three most common types of instances offered by Amazon Web Services (AWS) are on-demand, reserved, and on-site instances.

In an on-demand scenario, a user pays for the computer resources they use on an hourly basis without making any long-term obligations. These instances are typically used to specify requirements and manage spiking workloads. Compared to other types of instances, the cost of an on-demand instance is extremely high.

In contrast, the user must pay a one-time fee for committed utilisation for reserved instances. Typically, the provider provides significant discounts on reserved instances in an effort to draw in more clients.

In order to make use of their extra capacity, Amazon Web Services (AWS) has launched new sorts of instances called spot instances. In addition to supply and demand, there are a number of other factors that affect the price of the Spot instance. To obtain the instance, the user must put a bid. The majority of time-insensitive workloads, when the application or activity needs to run for a shorter amount of time, are handled by spot instances. According to estimates, AWS instances cost 30% less than on-demand and reserved instances. Users have trouble placing the bid at the best price because of the fluctuating pricing of AWS instances. Users must pay the higher price to use the on-spot instances if their bid amount is higher than the standard rates. On the other side, if the user makes a low bid price, he might not win the instance. Therefore, in this work, we have created an application that can forecast the best price for on-demand instances based on historical data analysis and other considerations like region, instance type, day and time, operating system, etc. With the aid of Python-Flask, a web application has been created where the idea of machine learning is being used for the best pricing prediction. Since this is a regression problem, we will use regression methods like linear regression, decision tree regression, and random forest regression in this study

2.Problem Definition and Objectives.

2.1 Feasibility Study:

Because there is a wealth of information on AWS Spot Instance prices and because machine learning techniques have been successfully applied to anticipate these costs, the study topic of AWS Spot Instances Pricing Prediction is quite practical. The following main points highlight the viability of this study topic:

1. **Data Availability:** AWS offers historical Spot Instance price information that is useful for developing and assessing machine learning models. Researchers may create and test models for various situations and use cases because of the data's availability at several granularities, including location, instance type, and time interval.
2. **Prior Research:** Using a variety of machine learning approaches, including regression analysis, decision trees, neural networks, and random forests, multiple research has been conducted on forecasting AWS Spot Instance costs. The validity of this study issue is supported by the encouraging outcomes of these investigations in properly forecasting Spot Instance pricing.
3. **Relevance and Importance:** Spot Instances provide significant cost savings for cloud users, and precise Spot Instance pricing prediction can assist users in successfully allocating their budget and optimizing their resource allocation plans. Because of this, the study's issue is very important and relevant in the context of cloud computing.
4. **Potential Impact:** Accurate Spot Instance price forecasting has the potential to significantly affect the cloud computing market by assisting cloud customers in cost- and resource-efficient resource allocation. As a result, cloud service providers may see an increase in income and better utilisation of their equipment.

2.2 Scope:

Future study and development have a great deal of possibilities for the research topic of AWS Spot Instances Pricing Prediction. Here are some probable future focus areas:

1. **Integration with Cloud Resource Management:** To optimise resource allocation and cut expenses, cloud resource management systems can be connected with spot instance pricing prediction. Future studies can concentrate on creating these tools and determining how effective they are.
2. **Real-Time Price Prediction:** To make forecasts for the future, current spot instance price prediction models are often trained on past data. The development of real-time prediction models that can update prices in real-time based on the state of the market can be the focus of future study.
3. **Multi-Cloud Prediction Models:** For their computing requirements, many organisations utilise a variety of cloud service providers. The development of multi-cloud prediction models that can forecast costs across various cloud providers and aid customers in optimising their resource allocation techniques can be the main goal of future research.
4. **Uncertainty Quantification:** Predicting Spot Instance prices is inherently uncertain because prices are affected by a variety of variables, including supply, demand, and availability. Quantifying uncertainty and creating models that can take uncertainty in price projections into account can be the main goals of future research.
5. **Integration with Spot Instance Marketplaces:** Users can bid on instance capacity on AWS' Spot Instance marketplace. To assist users in placing the best bids and streamlining their resource allocation tactics, future research can concentrate on integrating prediction models with these marketplaces.

2.3 Problem Statement :

It is challenging for users to adequately plan and budget their computing resources due to the very fluctuating and unpredictable cost of spot instances on the Amazon Web Services (AWS) cloud computing platform.

Spot instances are a reasonable choice for short-term workloads, but because of their market-based pricing, which can change quickly, there is a risk of service outages or unforeseen costs for customers. In order to help users make wise decisions and optimise their resource utilisation, a reliable and accurate technique to forecast the costs of AWS spot instances is required.

2.4 Objectives:

1. To analyze the factors that affect the AWS spot instances pricing, including date-time, region, operating system, and instance type.
2. To develop a predictive model that can accurately predict the price of AWS spot instances based on the identified factors.
3. To create an user interface that enables users to easily receive accurate predictions for spot instance prices from the given inputs.
4. To evaluate the effectiveness of different machine learning architectures, in predicting spot instance prices and identify the most accurate model.
5. To provide valuable insights into AWS spot instance pricing for users who wish to optimize their cloud resource usage and reduce costs.

3. Proposed Methodology:

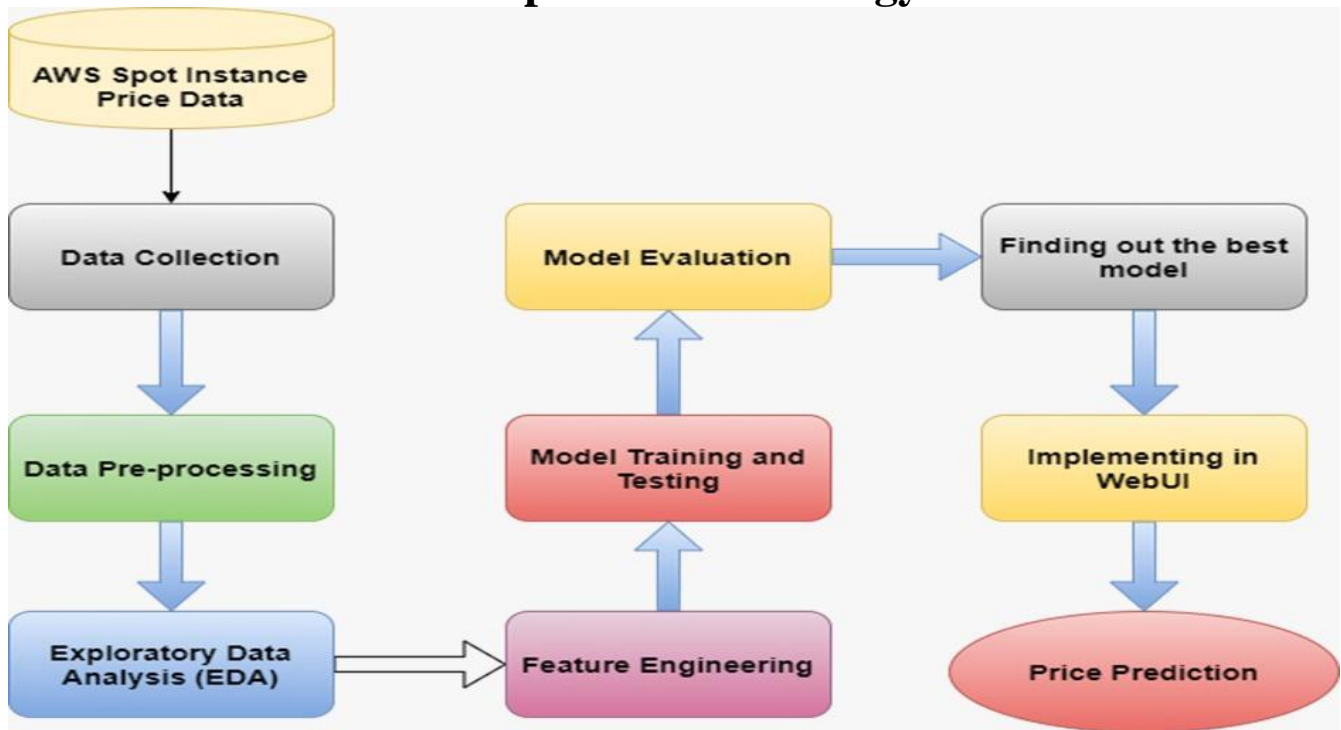


Figure 3.1. Flowchart

Data Pre-processing

In this step, the dataset is pre-processed and raw data is converted into a useful information. Data pre-processing also includes the data cleaning and data generalization steps. In the data cleaning steps, the null values are identified and handled. Also, the missing values from the dataset are also identified and filled with the mean of attribute value. As per our analysis, most of the data is clean and no missing values has been identified in the dataset.

Data Visualization

In order to perform the data visualization there are several set of python and spark libraries has been used, which includes the pandas, plotly, pyspark SQL functions etc. In order to writer the code in pyspark the spark is also installed in the virtual instance. The programming language used for development is pyspark. Jupyter notebook has been used as an interface to show the visualizations

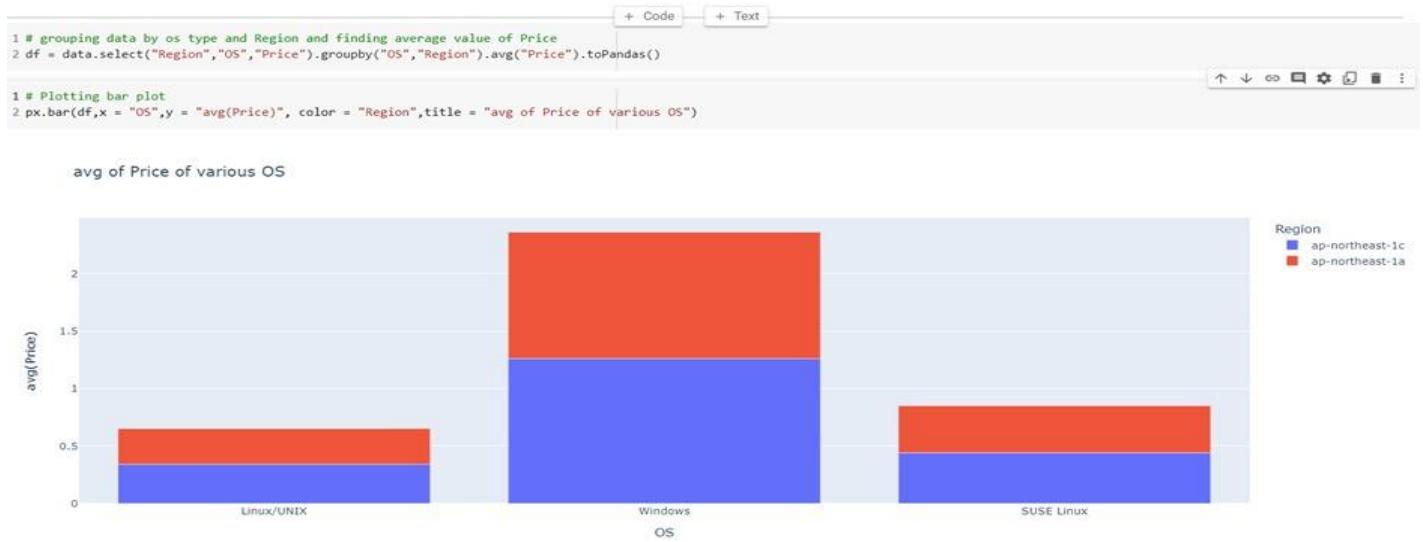


Figure 3.2. Grouping data by OS and Region and finding average price of AWS On-Spot Instance

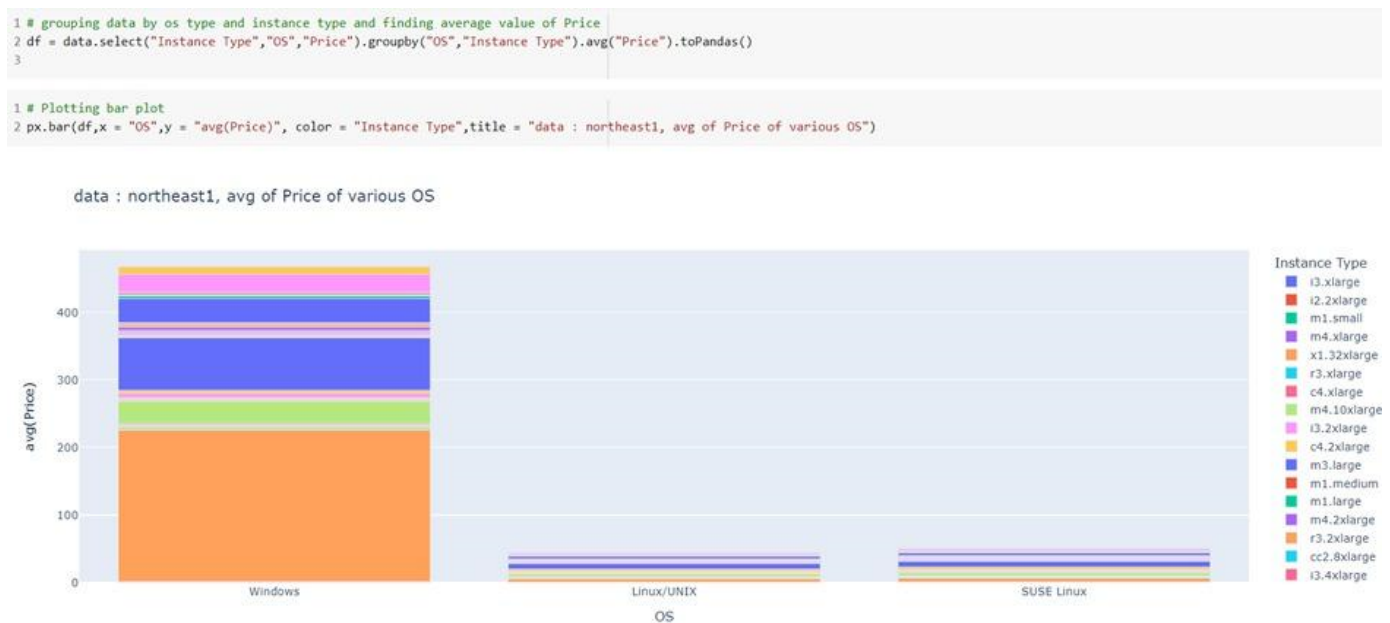
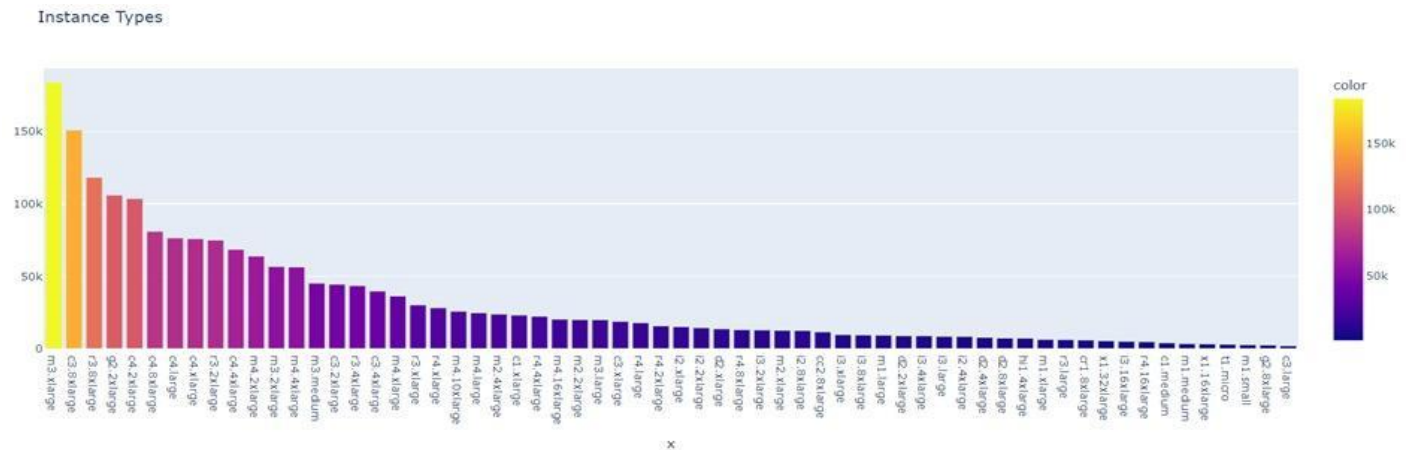


Figure 3.3. Grouping data by OS and instance type and finding average Price of AWS On-Spot Instance



On analyzing the frequency of each instance types it has been identified that m3.xlarge is highly used instance in the past, followed by c3.8xlarge. Therefore, we will further investigate and analyses the information about this instance.



Figure 3.5. Analyzing the price of m3.xlarge instance with respect to time over different Operating system

On analyzing the price of m3.xlarge instance with respect to time over different operating system it has been observed that the pricing of windows operating system is quite high as compared to the Unix/Linux and SUSE Linux operating system.

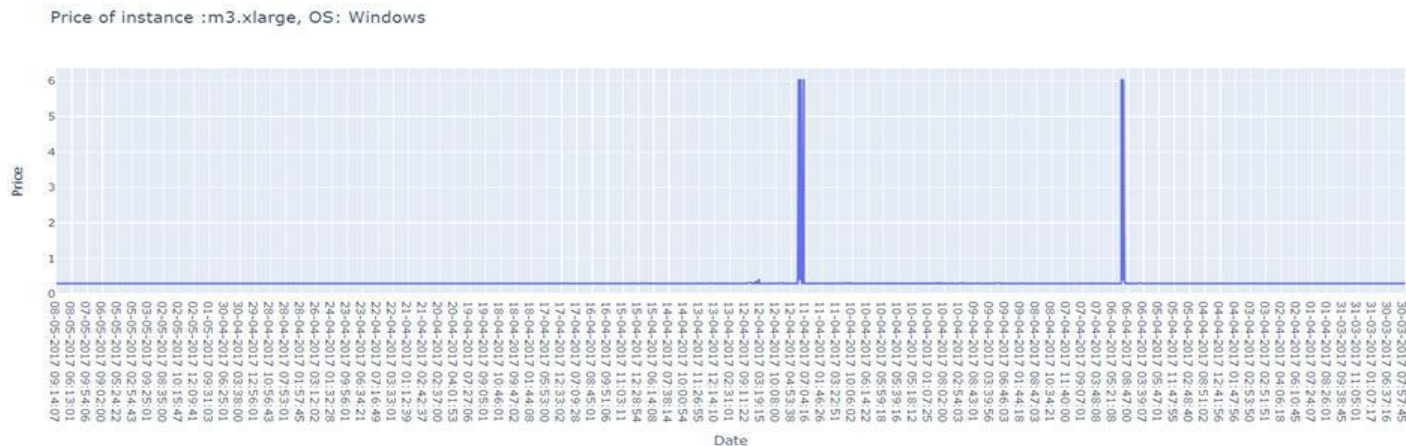


Figure 3.6. Analyzing the price of m3.xlarge with respect to time for windows operating system

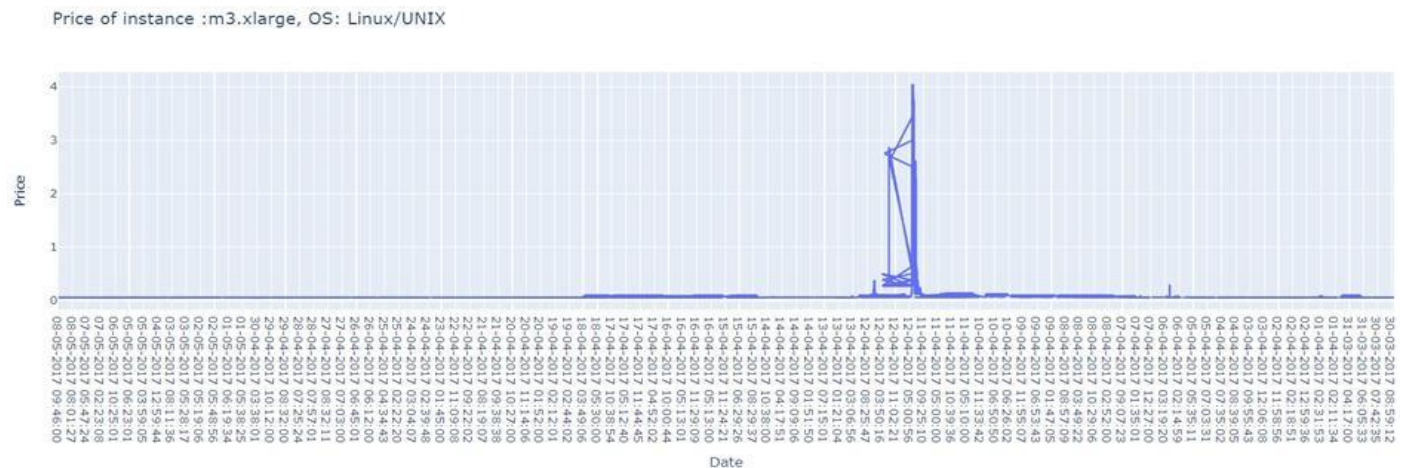


Figure 3.7. Analyzing the price of m3.xlarge with respect to time for Linux/UNIX Operating System

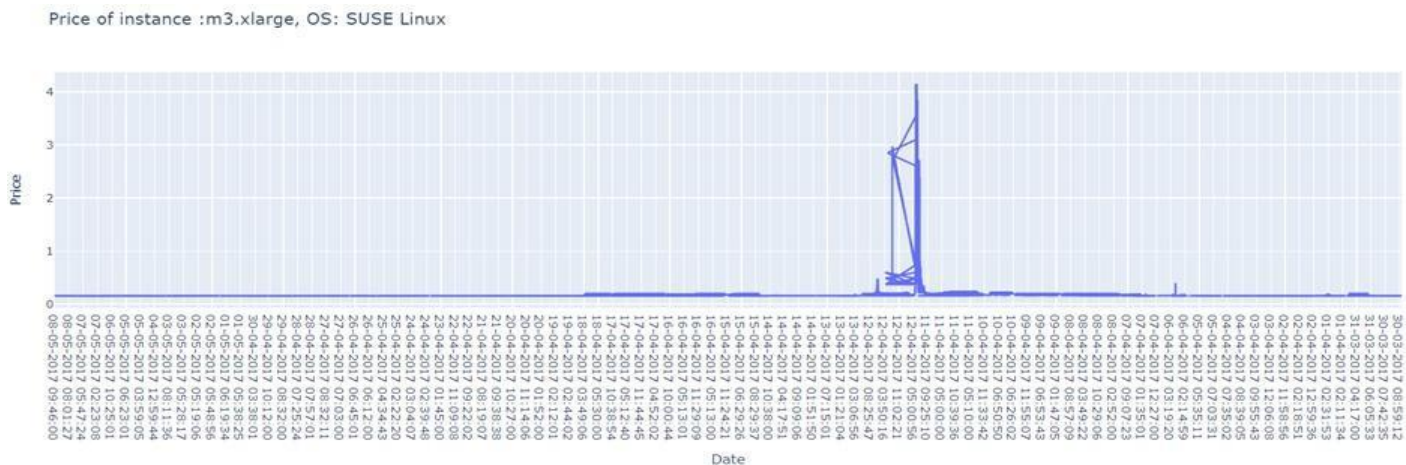


Figure 3.8. Analyzing the price of m3.xlarge instance with respect to time over SUSE Linux Operating system

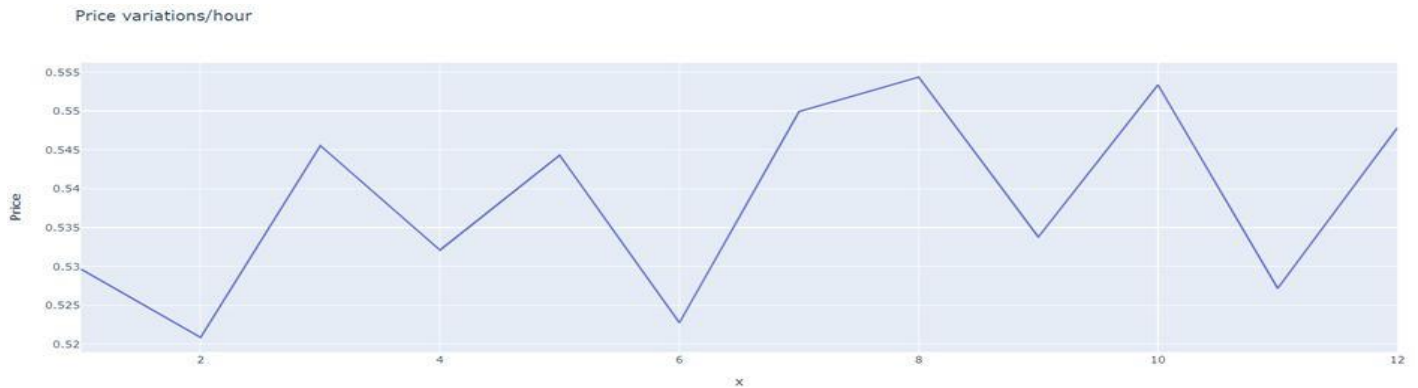


Figure 3.9. Price Variation of AWS On-spot instances based on Hour

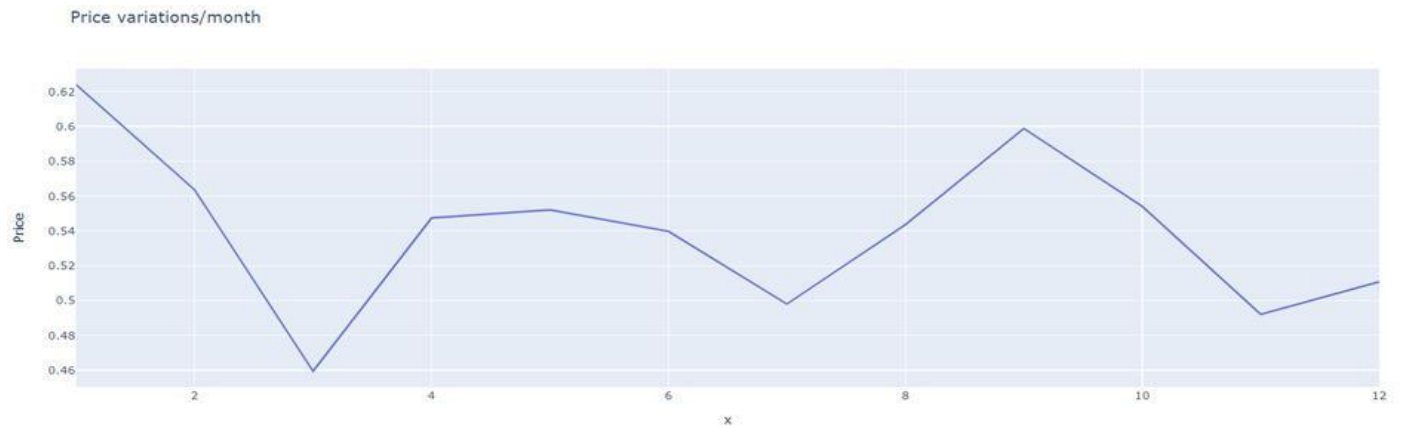


Figure 3.10. Price Variation of AWS On-spot instances based on Month

Model Training and Evaluation

In order to perform the future prediction from the obtained dataset model needs to be trained with the input features and target attributes. There are 3 different machine learning models will be utilized for this work. The models are Linear regression, decision tree regression and random forest regression. In order to train these models and evaluate the performance over the test, the obtained dataset needs to be splitted into training and testing set. Therefore, dataset has been divided with the ratio of 70:30. Where 70% of AWS On-spot instance price data can be used for model training and remaining 30% part can be used to evaluated the model performance over the testing data. There are two different performance metrics can be calculated over the test data to identify the most optimal model for accurate prediction. The performance metrics used for this project are Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The model having the minimum Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) score will be considered as most optimal model for prediction

Evaluation of Results

For identifying the most optimal algorithm, each algorithm has been trained over the training data and their training time has been calculated. Algorithms having the minimum training time will be considered as the most optimal algorithm. On the other hand, in terms of performance there are two metrics that have been calculated over the test data; those are Mean Square Error (MSE) and Root Mean Square error (RMSE). Model having the minimum MSE and RMSE score will be considered as the most optimal model.

	Time
Linear Regression	20.333251
Decision Tree Regression	36.663308
Random Forest Regression	62.972109

Figure 3.11. Training time Analysis of Machine learning Algorithms

After analyzing the training time of machine learning algorithms, it has been observed that linear regression algorithm takes the minimum time to train. Based on this metrics its difficult to derive the most optimal algorithm. Therefore, calculating the performance metrics is another criterion to identify the most optimal algorithm for prediction. This can be performed by calculating the MSE and RMSE score. The highest RMSE and MSE score has been obtained using Linear regression algorithm. Whereas, the minimum RMSE and MSE score has been obtained from Decision tree algorithm. Thus, it can be clearly said that decision tree is the most optimal algorithm for AWS on-spot price prediction with minimum error

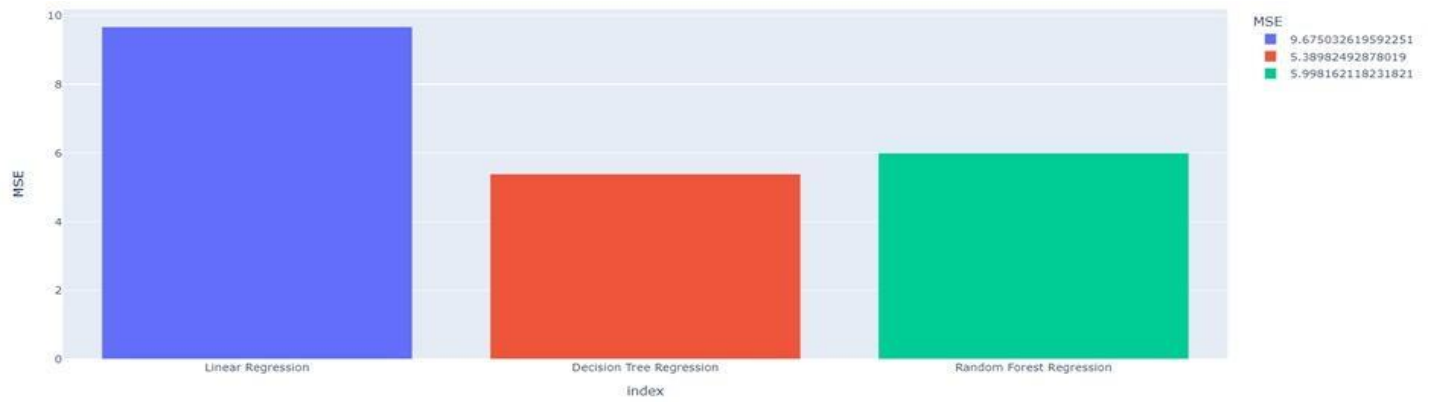


Figure 3.12. Comparison of Mean Square Error (MSE) between Machine Learning Algorithms

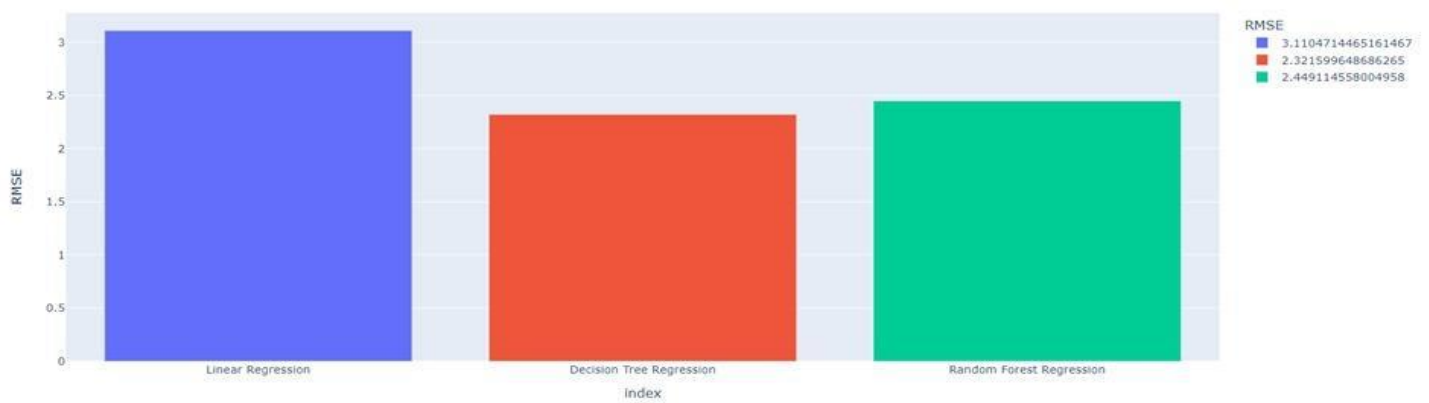


Figure 3.13. Comparison of Root Mean Square Error (RMSE) between Machine Learning Algorithms

After we decide the algorithm to be used, we now move on to the execution part.

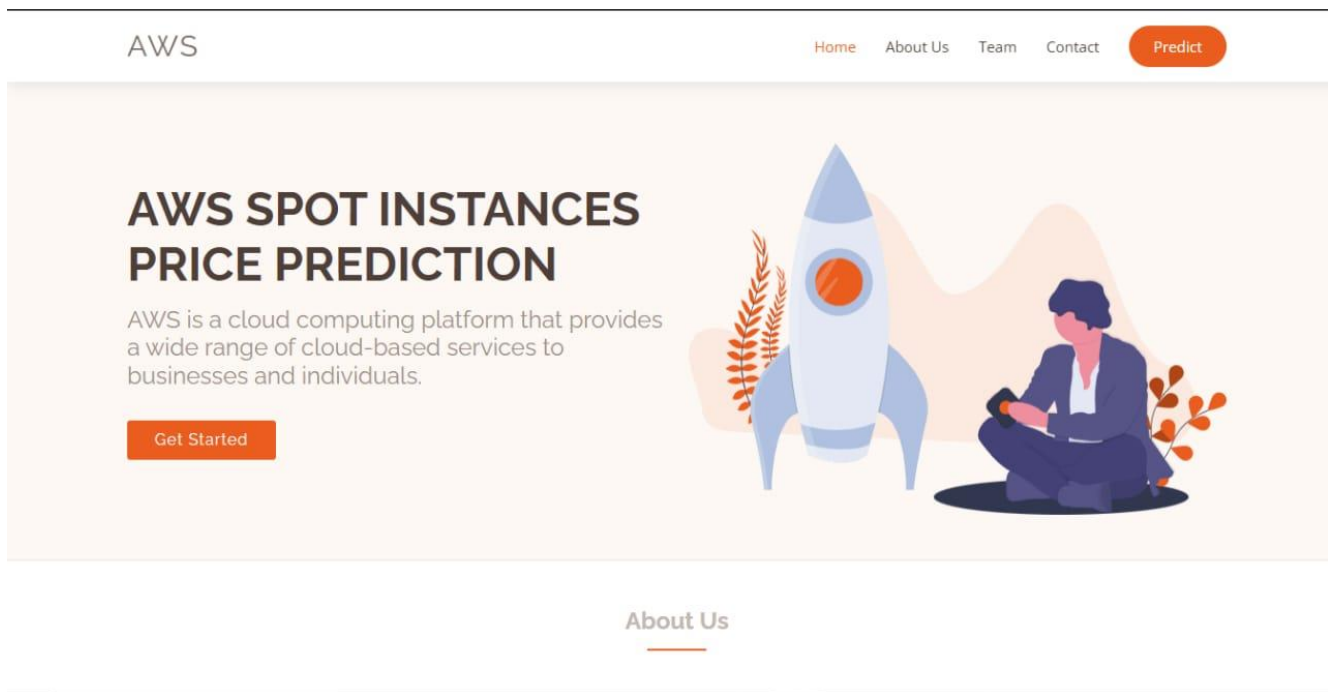
- Once the Spark application is started successfully, our web application can be executed by the following command:

```
python app.py
```

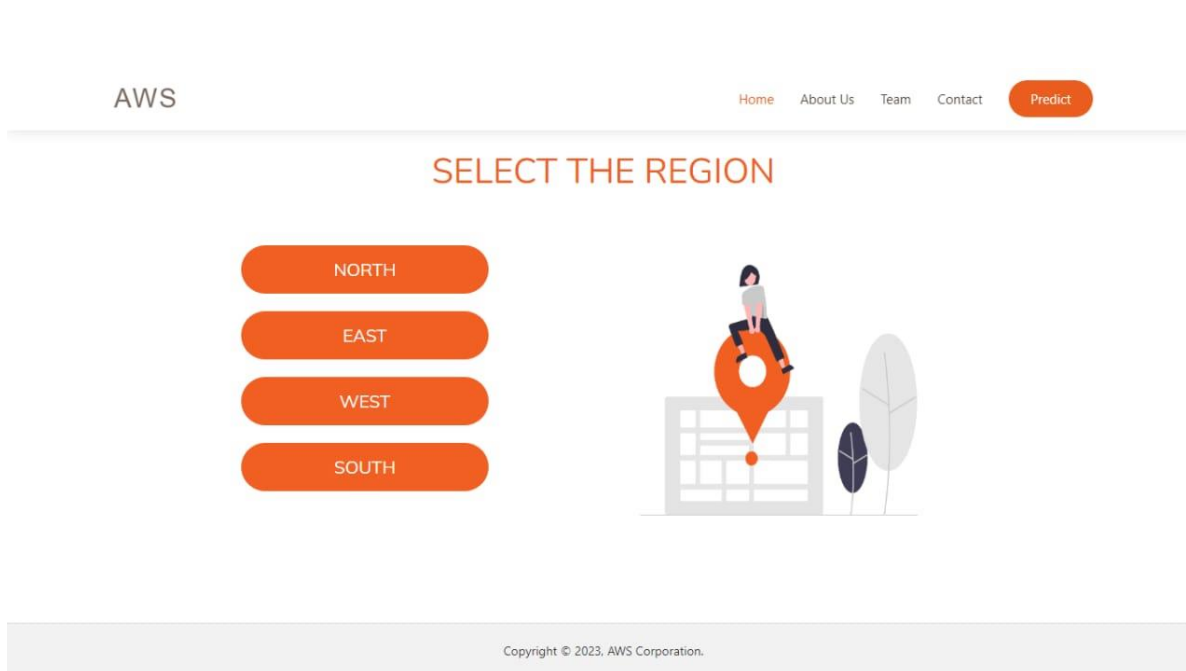
- Once the application is successfully executed, a web link will be generated (<http://127.0.0.1:5000/>).

```
Masterhadoop@master:~/Desktop/AWS_SPOT_INSTANCE_APPS$ python3 app.py
22/11/27 23:51:05 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable
Using Spark's default log4j profile: org/apache/spark/log4j-defaults.properties
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
* Serving Flask app 'app' (lazy loading)
* Environment: production
  WARNING: This is a development server. Do not use it in a production deployment.
  Use a production WSGI server instead.
* Debug mode: on
* Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
* Restarting with stat
22/11/27 23:51:13 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable
Using Spark's default log4j profile: org/apache/spark/log4j-defaults.properties
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
22/11/27 23:51:15 WARN Utils: Service 'SparkUI' could not bind on port 4040. Attempting port 4041.
* Debugger is active!
* Debugger PIN: 313-469-897
127.0.0.1 - - [27/Nov/2022 23:51:35] "GET / HTTP/1.1" 200 -
127.0.0.1 - - [27/Nov/2022 23:51:36] "GET /static/css/font-awesome.min.css HTTP/1.1" 304 -
127.0.0.1 - - [27/Nov/2022 23:51:36] "GET /static/css/style.css HTTP/1.1" 304 -
127.0.0.1 - - [27/Nov/2022 23:51:37] "GET /north HTTP/1.1" 200 -
127.0.0.1 - - [27/Nov/2022 23:51:37] "GET /static/css/font-awesome.min.css HTTP/1.1" 304 -
127.0.0.1 - - [27/Nov/2022 23:51:37] "GET /static/css/style.css HTTP/1.1" 304 -
127.0.0.1 - - [27/Nov/2022 23:52:08] "POST /predict HTTP/1.1" 200 -
127.0.0.1 - - [27/Nov/2022 23:52:08] "GET /static/css/font-awesome.min.css HTTP/1.1" 304 -
127.0.0.1 - - [27/Nov/2022 23:52:08] "GET /static/css/style.css HTTP/1.1" 304 -
127.0.0.1 - - [27/Nov/2022 23:56:06] "GET / HTTP/1.1" 200 -
127.0.0.1 - - [27/Nov/2022 23:56:06] "GET /static/css/style.css HTTP/1.1" 304 -
127.0.0.1 - - [27/Nov/2022 23:56:06] "GET /static/css/font-awesome.min.css HTTP/1.1" 304 -
127.0.0.1 - - [27/Nov/2022 23:56:08] "GET /north HTTP/1.1" 200 -
127.0.0.1 - - [27/Nov/2022 23:56:08] "GET /static/css/font-awesome.min.css HTTP/1.1" 304 -
127.0.0.1 - - [27/Nov/2022 23:56:08] "GET /static/css/style.css HTTP/1.1" 304 -
127.0.0.1 - - [27/Nov/2022 23:56:24] "GET /north HTTP/1.1" 200 -
127.0.0.1 - - [27/Nov/2022 23:56:24] "GET /static/css/font-awesome.min.css HTTP/1.1" 304 -
127.0.0.1 - - [27/Nov/2022 23:56:24] "GET /static/css/style.css HTTP/1.1" 304 -
```

- Home Page will be displayed



- Now, click on predict and select the region (north)



- Enter the Input Feature to predict the price

AWS

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PREDICTION FOR NORTH REGION

PLEASE FILL REGION :

MONTH :

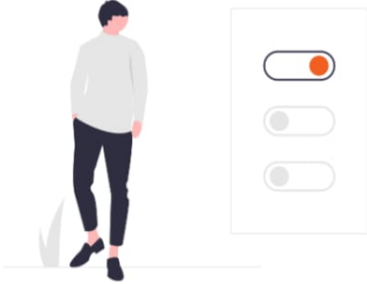
HOURLY :

OS INDEX :

REGION :

INSTANCE :

PREDICT



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- Predicted Price Outcome

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AWS SPOT INSTANCES PRICE PREDICTION

Price Prediction

Prediction for **north** region

Operating System : **Windows**

Instances : **p2.xlarge**

\$0.2614571443489008

Back

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3.2 Facilities required for proposed work:

In order to develop the application platform, the backend programming language has been used as pyspark. Where the flask web framework has been utilized to develop the front-end. Along with the flask, there are other technologies such as HTML, CSS and Javascript has been used. For utilizing the machine learning algorithms, the MLlib library of spark has been used. In order to save the model for prediction pickle library has been used. For visualization of data plotly and matplotlib library has been used extensively. Ubuntu operating system has been used to run the application. In order to run the application apache spark installation is required. After successfully installing apache spark, the spark application be started.

4. Literature Review:

Sr. No	Title	Paper-Year	Work
1.	Analyzing AWS Spot Instance Pricing	IEEE - 2019	<p>In this paper the data collection process involved using a custom-built tool that queried the AWS API every five minutes to retrieve the current spot prices for a range of instance types and availability zones and the raw pricing data was preprocessed to remove outliers. The paper shows that the pricing of spot instances varies significantly over time, with some instances experiencing fluctuations of over 100% within a single day. The availability zone in which an instance is launched has a significant impact on its pricing, with some zones consistently priced higher than others. The paper proposed a predictive pricing model that achieved an average prediction error of less than 2%, which could be used to inform resource allocation decisions.</p>
2.	Exploring Amazon EC2 Spot Instance Pricing Across Geographical Regions.	IEEE- 2018	<p>The paper aims to understand the factors that influence pricing and to identify regions that offer the most cost-effective solutions for resource allocation. The authors proposed a framework for predicting spot instance pricing across different regions. The proposed framework takes into account historical pricing data, region-specific factors such as availability of resources, and global</p>

			factors such as changes in demand for resources.
3.	Performance and Behavior Characterization of Amazon EC2 Spot Instances	IEEE - 2018	The paper provides a detailed analysis of the behavior of spot instances under different conditions, and presents guidelines for selecting instance types and bidding strategies. the paper provides valuable insights into the performance and behavior of Amazon EC2 spot instances, and offers practical recommendations for selecting and using spot instances for scientific computing workloads
4.	Amazon EC2 Spot Price Prediction using Regression Random Forests	IEEE - 2017	The authors compare the performance of their approach with other popular regression techniques and evaluate the accuracy of their model using mean absolute percentage error (MAPE) and mean absolute error (MAE). The results show that the proposed approach outperforms other techniques and achieves an MAPE of 6.23% and an MAE of 0.0405 USD. Overall, the paper provides valuable insights into the use of machine learning techniques for Spot Instance price prediction and highlights the potential of regression random forests as an effective approach for this task.
5.	Price forecasting for spot instances in Cloud computing Zhicheng Cai a, *, Xiaoping Li b , Rubén	Science Direct - 2017	The paper analyzes the historical spot instance price data of Amazon Web Services (AWS) and uses it to predict future spot instance prices using three

	Ruiz c , Qianmu Li a		different methods: time series analysis, multiple linear regression, and artificial neural networks. The authors evaluated the accuracy of each method using various statistical measures and found that the artificial neural network approach outperformed the other two methods in terms of prediction accuracy.
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5. Summary

Predicting the price of AWS spot instances is an important task that has yet to be fully explored in research. The spot instance market is highly dynamic and influenced by various factors, including date-time, region, operating system, and instance type. The project highlights the significance of AWS On-spot instances, which offer cloud computing resources at a significantly lower price than on-demand instances, making it a popular choice for customers. The project addresses the challenge of predicting the price of these instances, which varies frequently based on market demand and supply. In this study, these factors were taken into account to develop a user-friendly application for predicting the price of AWS spot instances.

Linear regression for this type of prediction is relatively easy to understand and implement. Additionally, it can provide insights into the relationships between the various factors that impact the price of a spot instance and provides a practical solution for customers to optimize their use of cloud services. The linear regression model attempts to find a linear relationship between the price of the spot instance and these factors. Once the model has been created, it can be used to predict the future price of a spot instance given new input data.

References

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