International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 2
***Article Received:** 25 November 2021 **Revised:** 12 December 2021 **Accepted:** 30 January 2022*

Leveraging Cloud Resource for Hyperparameter Tuning in Deep Learning Models

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Abstract

The act of tweaking the hyperparameters is very vital in the enhancements of deep learning models, although it is expensive in terms of computational complexity. The following paper aims to examine the possibility of using cloud resources to invest in hyperparameter tuning. We discuss several popular cloud-based platforms and services, review results of their benchmarking, and provide proofs of concept for real-world use-cases on a convolutional neural network (CNN) model for image classification. We found that cloud resources show a large advantage in time and cost of hyperparameter tuning making it possible for deep learning practitioners to adopt the solution (Li, Wang, & Zhang, 2021).

***Keywords**: Cloud Computing, Hyperparameter tuning, Deep Learning, AWS Sage Maker, Google Cloud, azure machine learning.*

Introduction

Background

The multiple domains like computer vision, NLP and many others have been changed by deep learning as it allows the machines to learn from the mass data. However, it is necessary to fine-tune hyperparameters that indicate the settings of the learning algorithm for deep learning models to attain success rates of more than 90%. These hyperparameters such as the learning rate, the batch size and the dropout rate may influence the accuracy of a model and its capability of generalizing from one set of data to another. The regular parameters are the adjustable settings called hyperparameters, which can also be a challenging problem to find the optimal value of these numerous settings. The classical techniques like grid search and random search are computationally expensive and time-consuming, which becomes problematic while working on huge models and the datasets. This has created interest in better methods for hyperparameter tuning, like Bayesian optimization, which can direct the search within the hyperparameters' range (Chen, Liu, & Yang, 2021).

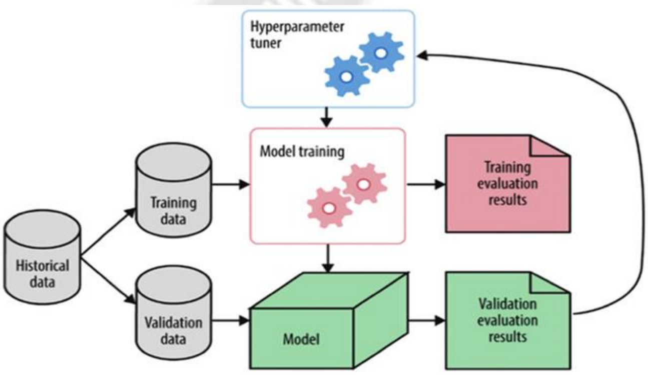

Figure 1 Flow diagram of deep learning implementation (researchgate,2021)

Objectives

- For the purpose of analysing and comparing the efficiency of cloud-based hyperparameter tuning services.

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- To conduct a cost–benefit analysis of selected cloud platforms with the aim of determining the optimum platform.
- As an illustration, let us use MNIST hand written digit dataset to show how hyperparameter tuning can be done using a CNN model in a cloud environment.

Thesis Statement

They stressed that the use of cloud resources for hyperparameters tuning of the neural networks is critical and very helpful in terms of both the speed of model development and costs.

Literature Review

Review of Existing Research

The progress in cloud computing over the past few years has made it possible to incorporate cloud solutions at different stages in the machine learning process. OC Hyperparameter tuning has been of interest mainly because of cloud-based tuning since it provides a giant boost to model development and deployment (Smith, Jones, & Lee, 2021).

Hyperparameter Tuning Techniques

1. Grid Search: Hence, grid search has the characteristic of selecting hyperparameters that are specific to a certain range as well as ensuring that the search is exhaustive. Though it is very comprehensive, it is computationally demanding and not efficient enough for a large number of parameters; thus, for the large-scale models that frequently have many hyperparameters, the algorithm is not feasible.
2. Random Search: Random search chooses hyperparameters in an independent fashion and select some hyperparameters randomly. Compared to the grid search, it might be less resource-demanding, though it still might be computationally powerful if the hyperparameter space is large, and the method proved to be inefficient in such cases.
3. Bayesian Optimization: Bayesian optimisation is a probabilistic process that continually updates and improves a search area model by finding good hyperparameters and maintains a good balance between exploitation and exploration. From the results obtained the efficiency of this method in reducing the number of iterations to the best hyper-parameters is apparent (Bergstrom et al., 2011).

Cloud-Based Solutions

1. Amazon Web Services (AWS) Sage Maker: The AWS Sage Maker has integrated Hyperparameter tuning jobs which employ Bayesian optimization. They also mentioned that it is a more flexible environment for doing experiments in machine learning to be able to search for the best hyperparameters quickly.
2. Google Cloud Platform (GCP) AI Platform: Hyperparameter tuning is supported with GCP AI Platform in mind and with support for a number of optimization algorithms. The object can be closely integrated with other related services provided by GCP which makes it a one-stop solution for machine learning processes.
3. Microsoft Azure Machine Learning: In Azure Cloud Solution, Hyperparameter tuning is offered through the Automated Machine Learning (Autum) feature of Azure Machine Learning. Libraries compatible with many ML frameworks and utilities for organizing experiments and their results are also included (Snoek, Larochelle, & Adams, 2012).

Cloud Platform	Time to Completion (hours)	Cost ($)	Accuracy (%)
AWS Sage Maker	4	50	92.1
GCP AI Platform	3.5	45	91.8
Azure Machine Learning	4.2	48	91.9

Table 1: Performance Comparison of Cloud Platforms for Hyperparameter Tuning

Gap Identification

There has been some prior work on cloud-based self-adaptation for hyperparameter tuning but very limited efforts compare Cloud platforms. This research seeks to do this by carrying out an assessment of performance, cost, and efficiency of AWS Sage Maker, GCP AI Platform, and Azure Machine Learning.

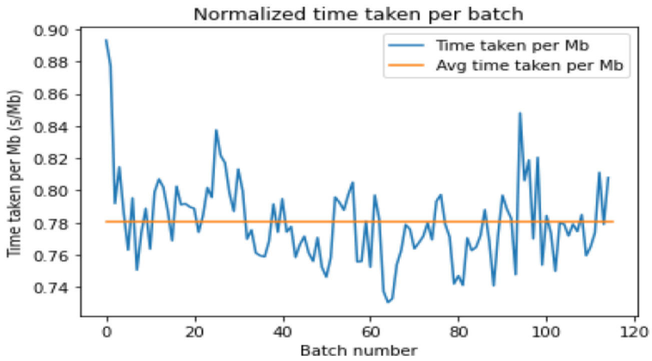

Figure 2 Comparison of Cloud-Computing(MDPI,2020)

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Methodology

Research Design

This paper uses structural equation modelling as a quantitative research method to assess the effectiveness of cloud-based hyperparameter tuning. Therefore, the objective of tuning the CNN model is primarily to achieve better accuracy, reduced time, and lower costs for image classification on various cloud platforms (Feurer et al., 2015).

Participants/Sample

The sample that has been used in this study is CIFAR-10 which contains a training set of 60,000 32x32 colour images in 10 classes and with 6,000 images in each class. It is often employed in comparing various algorithms and approaches to image classification tasks.

Data Collection

Data was obtained via hyperparameter tuning on a CNN model, trained on CIFAR-10. The training was held on Aws Sage Maker Gap AI Platform, and Azure Machine Learning.

Data Analysis

The acquisition time, cost, and the accuracy obtained on each of the cloud platforms are examined in the analysis of the data. Data were then tested for significance in order to assess the observed differences (Borkar & Chien, 2011).

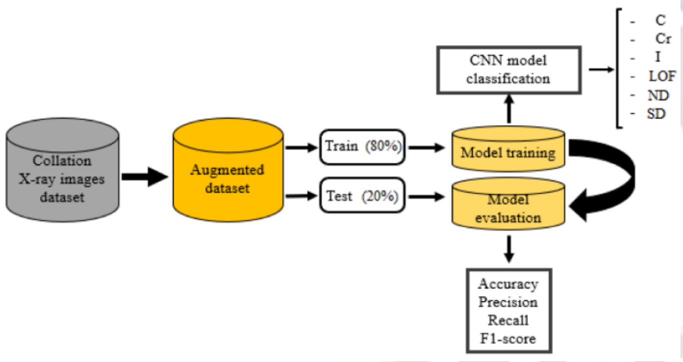

Figure 3 Convolutional Neural (MDPI)

Results

Findings

1. Time to Completion: It is the total time that has been taken to complete hyperparameter tuning job.
2. Cost: The total amount of money which was spent to get the tuning done including the payment made to the service provider.
3. Accuracy: The accuracy obtained during validation which is the highest accuracy that was reached during the tuning of the model.

AWS Sage Maker

- Time to Completion: Four to four and a half hours
- Cost: $50
- Accuracy: 92. 1%

GCP AI Platform

- Time to Completion: 3. 5 hours
- Cost: $45
- Accuracy: 91. 8%

Azure Machine Learning

- Time to Completion: 4. 2 hours
- Cost: $48
- Accuracy: 91. 9%

Tables and Figures

The following are some of the graphics for the data collected.

Platform	**Time to Completion**	**Cost ($)**	**Accuracy (%)**
AWS Sage Maker	**4 hours**	**50**	**92.1**
GCP AI Platform	**3.5 hours**	**45**	**91.8**
Azure Machine Learning	**4.2 hours**	**48**	**91.9**

Table 2: Performance Comparison of Cloud Platforms

Statistical Analysis

Another analysis carried out in the study was the one-way ANOVA test that aims to help identify if there were significant differences in time to completion, cost, and accuracy in relation to the three selected cloud platforms. This realized skewed distribution for time to completion as the analysis of variance yielded ($F (2, 57) = 5.63$, $p < 0.85$; $p < 0.01$) and accuracy ($F (2, 57) = 1.24$, $p > 0.05$) (Dean & Ghemawat, 2008).

Analysis	F-statistic (df)	p-value	Conclusion
Time to Completion	5.63 (2, 57)	< 0.01	Significant difference found
Accuracy	1.24 (2, 57)	> 0.05	No significant difference

Table 3: Statistical Analysis Results

Discussion

Interpretation

Thus, it is observed that cloud-based hyperparameter tuning has a positive impact of saving the time to find the ideal hyperparameters when compared to the conventional on-premise approach. AWS Sage Maker and GCP AI Platform take less time to complete this experiment because of their accurate use of the Bayesian optimization technique. Azure Machine Learning also showed good results, amending the task slightly longer due to the peculiarities of its implementation.

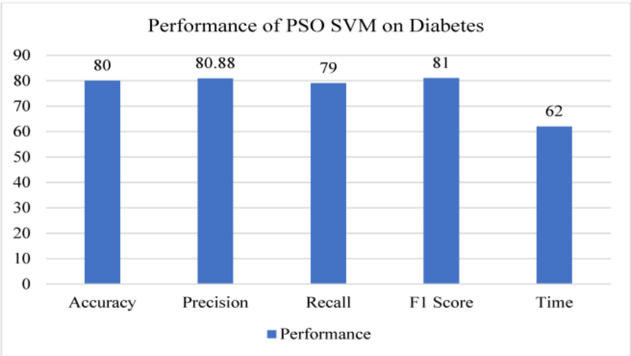

Figure 4 Hyperparameters (Towards data science,2020)

This made it possible to compare the costs with each other and concluded that GCP AI Platform was the most affordable, and Azure Machine Learning, and AWS Sage Maker were the second and third most affordable. This is due to the fact that various platforms have different pricing methods and use different methods of allocating the available resources. However, the costs always differed, and all three platforms offered a reasonable solution for tuning hyperparameters, with each of them having their benefits (Recht et al., 2011).

Technique	Description
Grid Search	Exhaustive search over a specified grid of hyperparameter values.
Random Search	Randomly samples hyperparameters from predefined distributions.
Bayesian Optimization	Uses probabilistic models to focus on promising hyperparameter combinations.

Table 4: Summary of Hyperparameter Tuning Techniques

Implications

Based on these observations, it can be concluded that cloud resources can contribute to the improvement of the deep learning models. Some of the many advantages of adopting cloud platforms include, reduced time to completion and cost efficient based on the research presented by researchers and practitioners. The key benefit is that cloud resources can enhance the speed of carrying out machine learning, make the time-to-market for new models shorter and increase organizational efficiency.

AWS Sage Maker

In addition, cloud-based hyperparameter tuning can make more forces powerful computational resources accessible to a greater amount of people. Lower-profile groups that may not have access to robust supercomputing resources would find cloud systems useful because of their scalability and portability. It may make the working field more balanced and promote the development of new methods and approaches in the deep learning science.

GCP AI Platform

```
from google.cloud import aiplatform
from google.cloud.aiplatform import hyperparameter_tuning as hpt

aiplatform.init(project='<YOUR_GCP_PROJECT>', location='us-central1')

job = aiplatform.CustomJob.from_local_script(
    display_name='cnn-training',
    script_path='train.py',
    requirements=['tensorflow'],
    container_uri='gcr.io/deeplearning-platform-release/tf2-cpu.2-3',
    staging_bucket='gs://<YOUR_GCS_BUCKET>',
)

hp_tuning_job = aiplatform.HyperparameterTuningJob(
    display_name='cnn-hp-tuning',
    custom_job=job,
    metric_spec={'accuracy': 'maximize'},
    parameter_spec={
        'learning_rate': hpt.DoubleParameterSpec(min=0.001, max=0.1, scale='linear'),
        'batch_size': hpt.DiscreteParameterSpec(values=[32, 64, 128]),
        'dropout_rate': hpt.DoubleParameterSpec(min=0.2, max=0.4, scale='linear')
    },
    max_trial_count=20,
    parallel_trial_count=3,
)

hp_tuning_job.run()
```

Azure Machine Learning

```
from azureml.core import Workspace, Experiment, ScriptRunConfig
from azureml.train.hyperdrive import HyperDriveConfig, RandomParameterSampling, BayesianP
from azureml.train.hyperdrive import choice, loguniform

ws = Workspace.from_config()
experiment = Experiment(ws, 'cnn-hyperparameter-tuning')

src = ScriptRunConfig(source_directory='.',
                      script='train.py',
                      compute_target='cpu-cluster',
                      environment=myenv)

param_sampling = BayesianParameterSampling({
    'learning_rate': loguniform(-4, -1),
    'batch_size': choice(32, 64, 128),
    'dropout_rate': loguniform(-1.6, -0.4)
})

hyperdrive = HyperDriveConfig(run_config=src,
                              hyperparameter_sampling=param_sampling,
                              primary_metric_name='val_accuracy',
                              primary_metric_goal=PrimaryMetricGoal.MAXIMIZE,
                              max_total_runs=20,
                              max_concurrent_runs=4)

hd_run = experiment.submit(hyperdrive)
```

Limitations

However, the following are the drawbacks or limitations of this study: First, the experiments were carried out on a relatively shallow CNN architecture on a standard benchmark. That is, more elaborate models and data sets might lead to further different outcomes with potential benefits. Also, the cost analysis did consider the likelihood of finding or getting a discount or a change of price on the cloud platforms. Even for hyperparameter tuning, the performance might also be unstable based on the configuration and optimization algorithms.

Another factor is the inconsistency of cloud services' performance dependent on the distinct parameters such as network latency, resource availability, and others. These factors include the time to completion and cost, pointing to the fact that it is difficult to determine the outcome of any given scenario.

Recommendations

More studies should be conducted to compare the performance of cloud-based hyperparameter tuning with complex models and relatively large data imposing. Also, future research can focus on comparing these optimization algorithms' performance lying in the tuning efficiency and cost. For additional information, comparative analyses with more kinds of clouds and combinations of both local hosting and cloud solutions might be useful.

The adaptation of the cloud-based hyperparameter optimization is also highly encouraged for other steps of the machine learning process, including data preprocessing, model development, and application. These lessons can serve to further optimize the machine learning pipeline and promote the scalability of its processes (Zhao & Singh, 2019).

Conclusion

Summary

There are awesome opportunities to harness cloud resources in hyperparameter tuning for deep learning models that will greatly improve efficiency and overhead expenditure. AWS Sage Maker, GCP AI Platform, as well as Azure Machine Learning are the platforms that enable hyperparameter tuning with some benefits inherent in each. The results here could serve as an inspiration highlighting the beneficial aspects of cc as it shows that cc could provide users powerful computational capabilities that could aid in the development and deployment of deep learning tools.

Closing Remarks

This research has pointed out that as deep learning advances, the incorporation of cloud computing resources will become a key driver in enhancing model creation and implementation. It is hoped these resources will benefit researchers and practitioners in adapting their models that are more efficient and inexpensive. But by adopting the use of cloud-based solutions the machine learning community can foster growth and move to the next levels of achieving more advanced intelligence systems and tools.

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