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## Hyperparameter Tuning of Deep learning Models in Keras

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### Abstract

Hyperparameter tuning or optimization is one of the fundamental way to improve the performance of the machine learning models. Hyper parameter is a parameter passed during the learning process of the model to make corrections or adjustments to the learning process. To generalise diverse data patterns, the same machine learning model may require different constraints, weights, or learning rates. Hyperparameters are the term for these kind of measurements. These parameters have been trial-and-error tested to ensure that the model can solve the machine learning task optimally. This paper focus on the science of hyperparameter tuning using some tools with experimental values and results of each experiments. We have also documented 4 metrics to analyze the hyperparameter tuning results and benchmark the outcome.

The experimental results of two tools used commonly for deep learning models namely Keras tuner and AiSara tuner are captured in the article. All relevant experimental code is also available for readers in authors github repository. The metrics used to benchmark the results are accuracy, search time, cost and complexity and expalinability. The results indicate the overall performance of AiSara tuner in search time, cost and complexity and expalinability matrices are superior to keras tuners.

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Keywords: Deep Learning, Model tuning, Hyperparameters, Hyperparameter tuning, Keras, Keras tuner, AiSara tuner, Machine learning

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### 1. Introduction

Machine learning model tuning is usually a trial-and-error process through in which we change some hyperparameters, run the model on the data again with the objective of improving the performance to figure out which set of hyperparameters gives the best accurate model In my pursuit of building efficient deep learning models, the model tuning stage to get the best accuracy. In this paper accuracy-complexity balance depends on many hyperparameters and value of those parameters can have wide ranges. So, the challenge became clear. There is no single step that can give me one best solution. It involves several trials with hyperparameters and acceptable range of values. So we decided to master the science of tuning of deep learning models [1-4]. At first, we found a tuning approach using Keras Tuner. The example python script found in google colab was very useful. Soon we realized we have to go beyond Keras tuner as my goal was to design an efficient deep learning model. In this paper we found another tool called AiSara Tuner for tuning deep learning model.

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We have experimented with both the Keras tuners with various hyperparameters and benchmarked some measures to compare the tools. We have used fashion MNIST dataset and CIFAR-10 datasets for my experiments as it is convenient for anyone who wants to evaluate the tools from anywhere. The Table 1 shows different metrics used for benchmark. Fig.1 represents Images on Multiple layers of abstraction in deep learning [1].

Table1. Metrics used for benchmark

| Sr. No. | Measure             | Explanation  |
|---------|---------------------|--|
| 1       | Accuracy (in %)     | Highest accuracy obtained by the tuner with same set of parameters set by inputs   |
| 2       | Search Time         | Time taken by the tuner to get the search spaces and return the best parameters.   |
| 3       | Cost and Complexity | The best set of parameters that minimizes the cost and maximises accuracy. Total number of learnable parameters will generally provide a pointer to computation cost in the training or prediction process. Fewer number of learnable parameters lower the computation cost. |
| 4       | Expalinability      | How easy to explain the results from tuners.   |

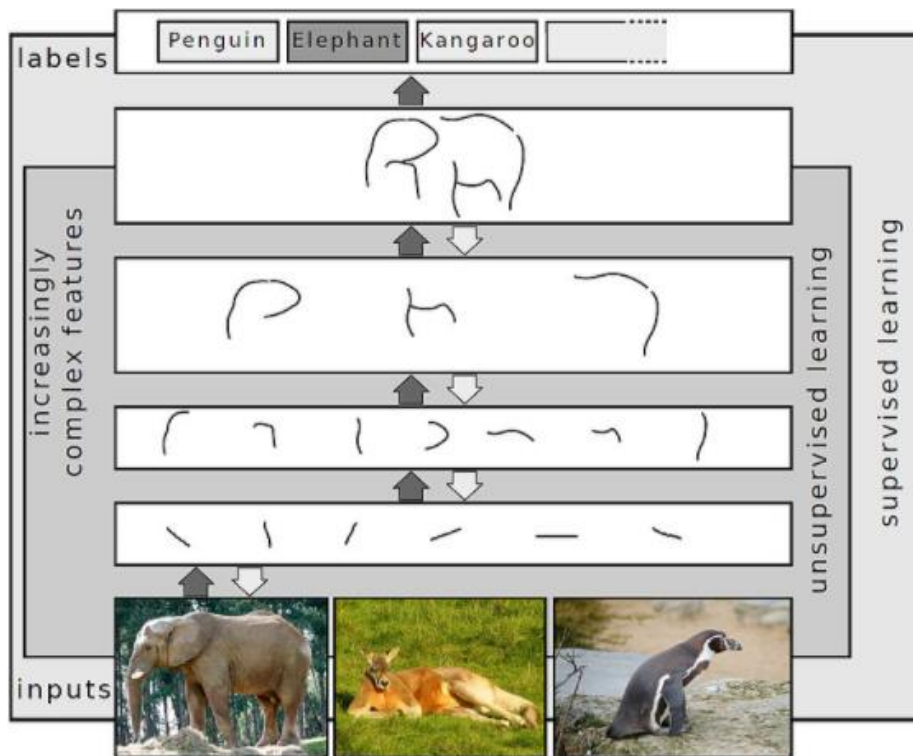


Fig. 1. Representing Images on Multiple Layers of Abstraction in Deep Learning [1]

## 2. Methodology and Experimental Setup

In this paper we have chosen a basic experimental dataset to enable all reviewers and learners to easily understand and verify the results by using commonly available dataset [5-6]. So the scripts provided here can be executed from Google Colab by anyone from anywhere. All the experiments are run in Google Colab and shared in my GitHub repo here [7-8].

## 2.1 System Environment

We have set Google Colab with Runtime hardware accelerator = "GPU" (Menu command Navigator: Runtime Change runtime type) [9-10]

## 2.2 Dataset

fashion MNIST dataset

```
import tensorflow as tf
from tensorflow import keras
```

```
# load fashion_mnist dataset
(img_train, y_train), (img_test, y_test) = keras.datasets.fashion_mnist.load_data()
```

CIFAR-10 dataset

```
(img_train, y_train), (img_test, y_test) = keras.datasets.cifar10.load_data()
```

## 2.3 Tuners

### Keras tuners

We have separately set up mirror environment to Keras tuner and AiSara tuner in separate python scripts.

### Keras tuner

Source of the python installer package: <https://pypi.org/project/keras-tuner/>

```
!pip install -q -U keras-tuner
import kerastuner as kt
```

### AiSara tuner

Source of the python installer package: <https://pypi.org/project/aisaratuners/1.1/>

```
!pip install aisaratuners
from aisaratuners.aisara_keras_tuner import Hp, HpOptimization
```

## 2.4 Hyperparameters

We have used 3 hyperparameters number of layers, number of units, learning rate in my experiments.

```
# define Hps:
hps = Hp()
hp_1 = hps.numrange(name='num_layers',min=2,max=10)
hp_2 = hps.numrange(name='nodes_dense',min=64,max=512)
hp_3 = hps.numrange(name='learning_rate',min=0.0001,max=0.01, type='log')
```

### 3. Experimental Results

The Fig. 2 shows the summary of all experimental results. Anyone can refer to GitHub report to view the source and results obtained from test runs.

| SI no | Measure             | DNN Model   |              | CNN Model   |              | Pre-trained Model |              | Overall Performance  |
|-------|---------------------|-------------|--------------|-------------|--------------|-------------------|--------------|--|
|       |                     | Keras-tuner | AiSara-tuner | Keras-tuner | AiSara-tuner | Keras-tuner       | AiSara-tuner |  |
| 1     | Accuracy (in %)     | 87.91       | 87.46        | 92.7        | 92           | 84.3              | 83.4         | Both tuners can provide same level of accuracy   |
| 2     | Search time         | 3m 40s      | 2m 18s       | 8m 39s      | 5m 46s       | 21m 46s           | 7m 33s       | AiSara is faster by 2X   |
| 3     | Cost and complexity | 143,905     | 110,515      | 4,633,455   | 1,968,071    | 15,503,962        | 14,826,315   | AiSara can produce best model with 20% fewer number learnable parameters   |
| 4     | Explainability      | Limited     | Excellent    | Limited     | Excellent    | Limited           | Excellent    | AiSara tuner has built in functionality to visualize search space and results graphically as well as tabular format.<br><b>AiSara is a clear winner with excellent presentation of search space and results.</b> |

Fig. 2. Experimental Results

AiSara Keras tuner has excellent graphical visualization methods which can explain the search space. Few samples of visualizations provided by AiSara keras tuner shown below in Fig.3.



Fig. 3: Graphical visualization of aisasartuner search space

Fig. 4 explains the tabulated results of aisaratuner search space with optimization results.

```
[11] # aisara tuner optimization results in dataframe
print(demo.opti_results)
```

|  | num_layers_conv | nodes_dense | lr       | loss     | acc      | val_loss | val_acc | Round   | model ID  |
|--|-----------------|-------------|----------|----------|----------|----------|---------|---------|-----------|
|  | 3               | 467         | 0.001000 | 0.086302 | 0.969083 | 0.253831 | 0.9256  | Round_1 | model_1_1 |
|  | 6               | 198         | 0.000158 | 0.135081 | 0.951233 | 0.213033 | 0.9249  | Round_1 | model_1_2 |
|  | 9               | 109         | 0.002512 | 2.303002 | 0.097367 | 2.302709 | 0.1000  | Round_1 | model_1_3 |
|  | 4               | 378         | 0.000398 | 0.082916 | 0.969783 | 0.250761 | 0.9256  | Round_1 | model_1_4 |
|  | 8               | 288         | 0.006310 | 2.303475 | 0.098967 | 2.302868 | 0.1000  | Round_1 | model_1_5 |
|  | 2               | 481         | 0.000398 | 0.078862 | 0.971117 | 0.248421 | 0.9292  | Round_2 | model_2_1 |
|  | 5               | 430         | 0.000338 | 0.085207 | 0.968667 | 0.229261 | 0.9319  | Round_2 | model_2_2 |
|  | 3               | 378         | 0.000367 | 0.086249 | 0.967483 | 0.234544 | 0.9248  | Round_2 | model_2_3 |
|  | 6               | 326         | 0.000432 | 0.092117 | 0.965967 | 0.229248 | 0.9268  | Round_2 | model_2_4 |
|  | 4               | 275         | 0.000468 | 0.088487 | 0.967317 | 0.230943 | 0.9317  | Round_2 | model_2_5 |
|  | 5               | 432         | 0.000329 | 0.081729 | 0.969667 | 0.230290 | 0.9273  | Round_3 | model_3_1 |
|  | 6               | 426         | 0.000338 | 0.090452 | 0.967183 | 0.210800 | 0.9338  | Round_3 | model_3_2 |
|  | 5               | 430         | 0.000334 | 0.085069 | 0.968950 | 0.283692 | 0.9207  | Round_3 | model_3_3 |
|  | 5               | 428         | 0.000348 | 0.087272 | 0.968350 | 0.225598 | 0.9306  | Round_3 | model_3_4 |
|  | 4               | 434         | 0.000343 | 0.084674 | 0.969433 | 0.233769 | 0.9312  | Round_3 | model_3_5 |

Fig. 4. Tabulated results of aisaratuner search space with optimization results

#### 4. Conclusion

In this paper, we have reviewed the performance of the two popular hyperparameter tuning method using Keras tuner and AiSara tuner. We have used four metrics to benchmark the performance of the tuners. The results indicate the overall performance of AiSara tuner in search time, cost and complexity and expalinability matrices are better than keras tuners. This experiment will help all data science enthusiasts and deep learning buddies to understand the keras tuners.

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