Performance Evaluation and Application of Computation Based Low-cost Homogeneous Machine Learning Model Algorithm for Image Classification

W. H. Huang
Amazon Web Services
Seattle, WA, United States
willhuan@amazon.com

ABSTRACT

The image classification machine learning model was trained with the intention to predict the category of the input image. While multiple state-of-the-art ensemble model methodologies are openly available, this paper evaluates the performance of a low-cost, simple algorithm that would integrate seamlessly into modern production-grade cloud-based applications. The homogeneous models, trained with the full instead of subsets of data, contains varying hyper-parameters and neural layers from one another. These models' inferences will be processed by the new algorithm, which is loosely based on conditional probability theories. The final output will be evaluated.

CCS Concepts

- Computing methodologies → Machine learning

Keywords

ensemble, machine learning, computer vision, deep learning

1. INTRODUCTION

The application of neural network based machine learning models on modern industrial sectors expanded tremendously [1] in recent years. Specifically, researchers and engineers have great interests in image classification. Utilizing the cost effectiveness of cloud-computing, massive quantities of software embed machine learning models as a portion of the cloud infrastructure. Often times, the training of the models would be facilitated using cloud-based interfaces. A pre-trained model could be utilized as a foundation for feature extraction and would potentially save training time while improving the model's performance [2]. Other hyperparameters such as mini-batch size, learning rate, epoch and layer freezing for transfer learning are crucial factors to consider when the model is undergoing fine-tuning.

Section 2 illustrate the theoretical concepts that drove the research work as well as corresponding probability equations. Section 3 states the experimental setup along with the respective hyperparameters. Section 4 outlines the results of the methodology. Section 5 provides arguments for the results observed and the application of the proposal in a cloud-based infrastructure.

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1.1 Problem Statement

Model ensembles are very popular techniques to improve the overall inferences' performances [3] [4]. While multiple methodologies are openly available, the option of **only changing the computational algorithm** to process the models' prediction and yield improved result would be exceptionally attractive in the pragmatic engineering perspective.

1.2 Related Works

The application of model ensemble was proposed to improve accuracy to various branches of machine learning [5]. The computational model ensemble technique of averaging the models' predictions was a simple yet effective approach to resolve variances between different model's predictions [6]. This paper is scoped to evaluate a novel computational technique that is loosely based on the conditional probability theorem for improving model ensemble performance.

2. THEORETICAL FRAMEWORK

The proposition to rank the models' output predictions loosely based on the conditional probability theorem is the core concept that is applied to the post-processing of ensemble models in this work. Given a test image for inference, a model would output a list of potential categories with the respective confidences. As oppose to averaging the confidences for ensemble models and yield the category with the highest confidence, the proposition would be finding the category with lowest probability that the ensemble models inferred the image does not belong to the said category. This section will walk-through the conceptual idea and the mathematical model behind the proposition.

Starting from the ensemble models, assume there are N trained models with different hyperparameters, ranging from number of layers to mini batch sizes, for N is a real integer and > 2 . Given a list of predictions, P_1 , was yielded from model M_1 with validation accuracy of A_1 . Another prediction list P_2 was yielded from model M_2 with validation accuracy of A_2 . Finally, P_3 was yielded from model M_3 with validation accuracy of A_3 . The first step of the proposition would be iterating through each class, C_j , within P_1 , P_2 , P_3 and calculate the probability that the ensemble models inferred the test image not being class C_j . In another word, instead of gathering the models and finding out how confident the test image belongs to one class, the proposed method is finding how confident the test image does not belong to the said class.

As referred in Figure 1, each class in the prediction list is computed with the same class from other lists as shown with red and green boxes. Before going further with the computation, it is assumed the models are trained with varying hyperparameters or neural architectures that allow larger variations in the neural network

weights and biases between one another. This is also an important criterion for ensemble models. Using Figure 1 example, the red rectangles of class B has three probabilities from three models. In order to calculate the probability of the models correctly predict that the image is not class B, the following mathematical model is employed.

Figure 1. The confidence values are in bracket for the different categories or classes

$$P(C_1 \cap T_1) = P(C_1|T_1)P(T_1) \quad (1)$$

Where T1 refers to model 1, M1, is correct to predict a class and P(T1) equals A1 The conditional probability that M1 predicted class C1 is calculated via the probability of C1 given T1 multiply by the probability of T1

$$P(!C_{1_{e^*}}) = 1 - \prod_{n=1}^N P((C_{1_n}) \cap T_n) \quad (2)$$

Where e* means ensemble. In theory, the probability of the ensemble correctly predict that the test image not being class C1 would be calculated using (2). However, the proposition is loosely based on the probability model, thus, some modifications were performed to the equations and yield the algorithm as shown in the form of pseudo-code in Appendix A.

Notice that the maximum of the ensemble probabilities is picked for the class C1 in the algorithm. The concept is that the ensemble should estimate how unlikely the test image belongs to class C1 and select the maximum probability. Then the value will be compared with that of other categories. In the end, the category with the minimal probability of all the categories will be selected as output for the test image classification. Putting the concept into simple terms, the process could be thought of as a double negation. First, find how unlikely the test image belongs to each individual category. The lower the value would mean the more likely that the test image belongs to this category and vice versa. Then, amongst all the computed outputs, finding the most probable category meant the minimal outputs would be retrieved.

The quantitative values of the probabilities can only be used in the ranking and should not be referenced as the actual model confidence of the category. Further limitations will be discussed in later sections of the paper.

3. EXPERIMENTAL PROCEDURE

Amazon Web Services (AWS) is employed for the experimentation and development of the work discussed in this paper. Similar features or technologies could be interchanged or substituted with open source software or libraries.

3.1 Data Labelling

Caltech256 and IMFDB images were used in the experimentation. The data sets were segregated into three segments: training, validation and test. As the images are already categorized, segmentation of images data set occurred from each category for training, validation and testing, respectively. AWS S3 was used for storing the images into their respective folder categories and a python script was executed to pull the images into AWS SageMaker for training, validation and finally testing.

3.2 Model Training

AWS Sagemaker was employed to facilitate the training of the image classification model using the image data set in AWS S3. Similar training procedures can be performed using machine learning frameworks and libraries such as Tensorflow, PyTorch, Keras, Caffe, etc. Numerous runs were triggered using different hyper-parameters and six models were selected for the ensemble. The models were trained with the same data- set. The respective hyper-parameters for the models are listed in Table I. All models use pre-trained model as basis.

Table 1. Hyperparameters for the ensemble models.

Model	One	Two	Three	Four	Five	Six
layers	18	34	50	101	152	34
weighted loss	true	false	false	true	true	true
learning rate	0.002	0.004	0.001	0.001	0.001	0.001
mini batch size	128	128	64	64	64	32

3.3 Batch Transform and Post-processing

The test data set were inferred by the six models using batch transform process. The outputs were yielded in the format of lists with the list index corresponds to the category and the value being the confidence with a maximum and minimum value of one and zero, respectively. The outputs, or predictions, would be consumed by the proposed algorithm and yield the computed category. The predicted category would be compared with the expected category for that test image and there would either be a match or a mismatch. The result will be tallied up and divided by the total test data set and yield the ensemble performance as shown in Results IV Table II. The conventional method of averaging the models' predictions and yield the category with highest average confidence is also processed as a control comparison.

4. RESULTS

The results of batch transforms from Section 3.3 were processed and tallied to yield the overall performances of the conventional ensemble algorithm and the proposed algorithm.

Table 2. Comparison of the ensemble algorithms and the respective performances

Methodology	Performance (%)
Top Performing Model.	73.56
Averaging Prediction	77.88
Proposed Algorithm	79.81

Referring to Table II, the proposed algorithm has an approximated 1% increase in performance comparing with the conventional averaging algorithm based on the experimentation.

5. DISCUSSION

Based on the result of the proposed algorithm for ensemble models, the boost in performance would be consider rather significant. Only the computation algorithm is changed while the trained ensemble models were left untouched. The advantages of the proposed technique in terms of operational perspective are as follows:

- * Does not require increasing the training data set
- * Does not require further tuning of the hyper-parameters

The conventional ensemble algorithm tends to simplify the variances of between the ensemble models' inferences, thus, overlooked subtle patterns within the output data. The proposed algorithm provides more insight into the relationships between the predictions. In addition, the validation performance of individual model was also taken into consideration as seen in Appendix A. This would act as a weighted coefficient to further fine tune the relationships of the models in the ensemble.

Being able to use the models in their current state with only minor modifications to the overall system architecture would be a tremendous convenience in practice. The proposed technique is a low cost alternative for improving the ensemble performance. There are also obvious limitations when employing the proposed methodology and will be discussed as follows.

5.1 Limitation

The theoretical model is loosely based on specific concepts of the probability theories. Thus, the resulting probability values should only be used in a relative sense. That is, the values serve as references for ranking the predicted categories. Note that this same assumption holds true for the conventional ensemble algorithm.

5.2 Application

Integration into cloud-based systems would be easily achieved via the usage of Lambda functions containing the proposed algorithm. The advantage of the proposal became apparent since the technique is computational in nature and can be self-contained in a Lambda functions, which can be easily inserted into cloud infrastructure. Referring to Figure 2 The models, trained by AWS SageMaker, are being encapsulated by running instances such that AWS Lambda function could invoke them and retrieve the inferences from an

Figure 2. Integrating the algorithm in Lambda

input image requested by the service endpoint. The inferences would be processed by the proposed computational algorithm

within another Lambda function and yield the final output. The lambda would allow high concurrency and great scaling for the application.

6. CONCLUSION

Image classification is a major field in the machine learning sector. Other than tuning hyperparameters and increasing data set, ensemble models would be a great alternative to boost the overall performances. This paper investigated a novel ensemble computational algorithm based loosely on probability theories and demonstrated a % boost in performance comparing to the conventional computational ensemble technique. Although there are limitations and boundaries with regards to the theoretical aspect of the proposed technique, it would be sufficient to apply to most applications in practice.

7. APPENDIX

The following pseudo-code function would consume pre-diction lists from ensemble models and yield the predicted category.

```

/* In order to infer the category of the
test image the arguments are the each
model's list of confidences with the
associated category. For example,
model_1_pred = [0.1, 0.2, 0.44, 0.33]
where the index of the list
corresponds to the category which is
['class A', 'class B', 'class
C', 'class D'], for this example
there are a total of four classes. */

function
ensembleProbabilityAlgorithm(model_1_pred,
model_2_pred, ..., model_N_pred)
{ category_1_result
category_2_result
...
category_N_result

for index in range(length of
model_1_pred):
/* iterate through each index (category)
and compute the maximum probability
that the models predict the test
image not being the said category */
model_1_result = 1 -
model_2_pred[index] *
model_3_pred[index] * ... *
model_N_pred[index]
+ (1 - model_1_pred[index]) *
model_1_accuracy
/* model_1_result is equal to 1 -
(the probability of all the models
correctly predict the category)
plus the probability of model 1
predicting the test image not
being the current category times
the validation accuracy of model
1. */

model_2_result = 1 -
model_1_pred[index] *
model_3_pred[index] * ... *
model_N_pred[index]
+ (1 - model_2_pred[index]) *
model_2_accuracy

```

```

/* notice that for model_2_result
the third term is switched from
model_1_pred[index] to
model_2_pred[index] and the
model
2's validation accuracy
(model_2_accuracy). continue
through all the models */
...

model_N_result = 1 -
    model_1_pred[index] *
    model_2_pred[index] * ... *
    model_(N - 1)_pred[index]
+ (1 - model_N_pred[index]) *
    model_N_acuracy

category_(index)_result = the maximum
of {model_1_result,
model_2_result,
..., model_N_result}
/* the maximum of the probability for
the models prediction of the test
image not being in this category
is
    stored outside of the loop */

return the index of the minimum of
{category_1_result,
category_2_result,
..., category_N_result}
/* we are returning the category with
the
    least probability value of the
models "think" they predicted the
test image
not being this category this is a

```

```

double negation. In another word, for
each category, how confident are the
models think the test image is NOT
this category, then find the category
with the smallest values (least
confident that this is not the
category). The double negation will
yield the category for the test image
*/
}

```

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