Cascade Bagging for Accuracy Prediction with Few Training Samples

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Abstract

Accuracy predictor is trained to predict the validation accuracy of a network from its architecture encoding. It can effectively assist in designing networks and improving Neural Architecture Search (NAS) efficiency. However, a high-performance predictor depends on adequate training samples, which requires unaffordable computation overhead. To alleviate this problem, we propose a novel framework to train an accuracy predictor under few training samples. The framework consists of data augmentation methods and an ensemble learning algorithm. The data augmentation methods calibrate weak labels and inject noise to feature space. The ensemble learning algorithm, termed cascade bagging, trains two-level models by sampling data and features. In the end, the advantages of above methods are proved in the Performance Prediction Track of CVPR2021 1st Lightweight NAS Challenge. Our code is made public at: https://github.com/dlongry/Solution-to-CVPR2021-NAS-Track2

1. Introduction

Neural architecture search advances beyond the state-of-the-art in various computer vision tasks. However, it often trains and evaluates a large number of architectures, causing tremendous computation costs. For instance, Zoph et al.[15] spends more than 1800 GPU days and Real et al.[12] uses 450 GPUs for 7 days to train and evaluate the models. Thus, how to estimate the performance of a neural architecture in a fast and accurate way is vital for addressing the computational challenge of NAS.

Predictor-based evaluation strategy is one of the mainstream methods to reduce the computation overhead. It takes the architecture description as inputs and outputs a predicted performance score. Two factors are crucial to the predictor fitness: 1) embedding space; 2) regression model. To embed neural architectures into a continuous space and get a meaningful embedding space, many studies have proposed different encoders, such as sequence-based methods[10, 8, 13] and graph-based methods[2, 4, 11]. Several different regression models have been utilized to estimate the accuracy, including gradient boosting decision tree[9], gaussian process[7] and graph convolution network[4, 2].

In this paper, to reduce the computation burden of predictor-based evaluation strategy, we propose a novel framework to train accuracy predictor under few training samples. The framework consists of data augmentation with limited budget and ensemble learning for promoting generalization. In the end, the effectiveness of the framework was verified in the Performance Prediction Track of CVPR2021.
1st Lightweight NAS Challenge.

2. Method

For reducing the cost of NAS, we propose a novel framework to train an accuracy predictor under few training samples. To alleviate the high risk of overfitting caused by the lack of training data, the framework consists of data augmentation methods and an ensemble method termed cascade bagging.

2.1. Data Augmentation

We adopt weak label calibration and gaussian noise addition to augment dataset under limited computation overhead.

2.1.1 Label Calibration

Given two datasets \( S_r \) and \( S_w \). \( S_r \) only has few architectures with ground-truth labels \( Y_r \). \( S_w \) has more architectures with weak labels \( Y_w \). Weak labels are generated by insufficient training under limited overhead. Here, we calibrate the weak labels \( Y_w \) and make it close to the ground-truth label.

Two valid information are chosen to calibrate the weak labels. One is the difference between the mean values of \( Y_r \) and \( Y_w \). The other is the difference between the weak labels and the prediction results. Specifically, we divide the samples of \( S_w \) into \( N \) groups according to accuracy. We assume that the weak labels and ground truth labels have the similar biases. Based on the assumption, i-th weak label \( Y_w^i \) in a group can be calibrated with a function as follows:

\[
Y_w^i = Y_w^i + (E_r - E_w) + b \tag{1}
\]

\( E_r \) and \( E_w \) are the mean values of \( Y_r \) and \( Y_w \), respectively. \( b \) means modified bias, which is a hyper-parameter.

Referring to the ideas of semi-supervised algorithm [6, 14], we utilize the prediction results to correct weak labels with the following equation:

\[
Y_w^i = \alpha \cdot Y_w^i + (1 - \alpha) \cdot Y_{P_i} \tag{2}
\]

\( Y_{P_i} \) is the prediction result of i-th architecture. \( \alpha \) denotes a linear coefficient hyper-parameter. Note that, since a new predictor can be updated with modified labels. The new \( Y_{P_i} \) can be generated. The calibration process above can be made repeatedly. We find that the prediction results from multiple calibration processes benefit for final predictor performance.

2.1.2 Noise addition

Many studies[1, 14] have reported that adding noise to smooth feature space can improve model generalization ability. In this work, we utilize noise to enlarge training set with negligible cost. we firstly sample a data \((x,y)\) from training set. We then inject Gaussian noise to slightly perturb the feature \( x \) to get new feature \( x' \). Lastly, give the feature \( x' \) the same label \( y \) as \( x \), we can obtain new training data \((x',y)\).

2.2. Cascade Bagging

Traditional bagging algorithm has ability to promote models’ generalization[5]. Utilizing traditional bagging algorithm to train a predictor has two steps. Firstly, numerous sub training sets are created by sampling data from training set with replacement. Secondly, a series of weak predictors are trained with the sub training sets, respectively. In testing phase, the final prediction result is mean value of the predictors’ outputs. Traditional bagging algorithm ignores the fact that different predictors should make different contribution to final prediction result. For automatically calculating contributions of different predictors, we propose a cascade bagging algorithm in our framework.

As shown in Figure 2, we firstly train numerous first-level models with the sub training sets, which are the same as the traditional bagging algorithm. Secondly, we train second-level models using different combinations of features. As shown in the Figure 2(b), the combination features are consisted of two parts: 1)the first part features are sampled from the outputs of first-level models; 2)the second part features are architecture encoding after PCA dimension reducing.

In testing phase, we calculate the outputs of first-level models and reduce the dimension of architecture encoding. We concatenate the outputs and the dimension reduction features prior to inputting them into second-level models. Lastly, the second-level outputs are averaged as the final prediction result.

3. Experiment

In this work, we proposed a novel framework to train an accuracy predictor with few training samples. This section reports the effectiveness of the framework by various experiments.

3.1. Dataset

The dataset are supplied by CVPR2021 workshop NAS challenge. It contains 231 training samples. 200 samples have weak labels, which are obtained by training models with insufficient epoches. Other 31 samples have ground truth labels obtained by sufficient training.

3.2. Architectures Encoder

The architectures of the competition dataset are sampled from the Mobilenet-like search space, where 16 blocks are searchable. The 16 blocks are connected to each other in sequence. The choices of each block range from [1,6] which
means 6 (three choices of kernel size, two choices of expansion rate) different operations.

Based on the above space, we design a black-box and a white-box architecture encoding. Black-box encodes a network with 16-dimensional features, and the i-th dimension denotes the index of the operation of the i-th block. White-box encodes the network as a $2 \times 16$-dimensional tensor. Each block is represented by a two-dimensional vector which denotes its kernel size and expansion ratio.

### 3.3. Ablation Study

The experiments in Table 1 prove the validity of calibration labels with adding proper bias. These experiments base on Xgboost model. Method B1 only uses 31 samples with ground truth label. Compared to B1, B2 uses more 200 calibrated samples. The result of B2 presents huge improvement over B1, which illustrates adding proper bias is effective for label calibration. The performance of W3 is better than W2, indicating the validity of noise addition for generating new data. In addition, the results of B2 and W1 highlight that white-box is a better architecture encoder than black-box.

The experiments in Table 2 verify the effectiveness of weighting sum the prediction results for calibrating labels. The experiments base on SVM model and use traditional

| method | encode | g  | bias  | noise | RMSE |
|--------|--------|----|-------|-------|------|
| B1     | Black  | -  | -     | w/o   | 0.252|
| B2     | Black  | 1  | 2.2   | w/o   | 0.228|
| W1     | White  | 1  | 2.2   | w/o   | 0.212|
| W2     | White  | 3  | 2.24,2.2,2.22 | w/o | 0.204|
| W3     | White  | 3  | 2.24,2.2,2.22 | w    | 0.201|

Table 1. Ablation study of label calibration with eqn(1) and noise addition. "encode" means encoding type of architectures. "g" and "bias" means group number and value of $(E_r - E_w) + b$ in eqn(1), respectively. "noise" indicates whether noise is added to feature space.

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**Figure 2.** The training framework of the cascade bagging. (a) The training diagram of the first-level models. (b) The training diagram of the second-level models and testing process.
bagging algorithm, which train 100 models with random data sampling. Because of the above changes, the RMSE decreases from 0.201 to 0.1857. S2 and S3 calibrate the weak labels using Eqn(2) with 1 group and 3 group, respectively. The results show that prediction results are effective information to calibrate labels and multiple calibration processes also have positive effect on the final result. In addition, S5 utilizes prediction result from SVM and xgboost to correct the weak labels. Its results prove that using more models may further improve performance. However, S4 shows that this improvement does not persist for all models. The reason may be that label noise is introduced from poor prediction results.

| method   | models for calibration | iter | RMSE  |
|----------|------------------------|------|-------|
| S1       | -                      | -    | 0.1857|
| S2       | SVM                    | 1    | 0.1849|
| S3       | SVM                    | 3    | 0.1846|
| S4       | SVM,KNN                | 3,1  | 0.1849|
| S5       | SVM,Xgboost            | 3,1  | 0.1829|

Table 2. Ablation study of label calibration with eqn(2). “iter” denotes number of calibration times. In S4, it means the calibration times of SVM and KNN are 3 and 1 respectively.

The experiments in Table3 prove validity of cascade bagging. Besides training 100 first-level models, the cascade bagging trains more 100 second-level models. The second-level models enable to automatically calculate first-level models’ contribution. The results in the table show that cascade bagging can further enhance the predictor performance.

| method     | RMSE  |
|------------|-------|
| Bagging    | 0.1829|
| Cascade bagging | 0.1808|

Table 3. Ablation study of cascade bagging

The experiments in Table3 prove validity of cascade bagging. Besides training 100 first-level models, the cascade bagging trains more 100 second-level models. The second-level models enable to automatically calculate first-level models’ contribution. The results in the table show that cascade bagging can further enhance the predictor performance.

4. Conclusion

This work provides a novel framework to train an accuracy predictor under few training samples. The framework consists of data augmentation methods and a cascade bagging algorithm. By conducting experiments on different combinations of the training methods, we find that the prediction results and the mean value of ground truth label are valid information for label calibration. We also observe that injecting noises to feature space is able to generate effective data. In addition, our cascade bagging algorithm can automatically adjust the contribution of different predictors, which outperforms traditional bagging algorithm. Finally, combined with the above methods, our framework ranks the 3rd place in the Performance Prediction Track of CVPR2021 1st Lightweight NAS Challenge.

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