ENAS4D: Efficient Multi-stage CNN Architecture Search for Dynamic Inference

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Abstract
Dynamic inference is a feasible way to reduce the computational cost of convolutional neural network (CNN), which can dynamically adjust the computation for each input sample. One of the ways to achieve dynamic inference is to use multi-stage neural network, which contains a sub-network with prediction layer at each stage. The inference of an input sample can exit from early stage if the prediction of the stage is confident enough. However, design a multi-stage CNN architecture is a non-trivial task. In this paper, we introduce a general framework, ENAS4D, which can efficiently search for optimal multi-stage CNN architecture for dynamic inference in a well-designed search space. Firstly, we propose a method to construct the search space with multi-stage convolution. The search space includes different numbers of layers, different kernel sizes and different numbers of channels for each stage and the resolution of input samples. Then, we train a once-for-all network that supports to sample diverse multi-stage CNN architecture. A specialized multi-stage network can be obtained from the once-for-all network without additional training. Finally, we devise a method to efficiently search for the optimal multi-stage network that trades the accuracy off the computational cost taking the advantage of once-for-all network. The experiments on the ImageNet classification task demonstrate that the multi-stage CNNs searched by ENAS4D consistently outperform the state-of-the-art method for dynamic inference. In particular, the network achieves 74.4% ImageNet top-1 accuracy under 185M average MACs.

Introduction
Deep convolutional neural networks (CNNs) have demonstrated its powerful capabilities in computer vision tasks, such as image classification (He et al. 2016), object detection (Ren et al. 2015), and image segmentation (He et al. 2017). However, the performance of CNNs always comes with a huge computational cost. Thus, various methods have been proposed to reduce the computational cost of the CNN inference, including efficient network architecture design (Howard et al. 2017), network pruning (Han et al. 2015) and weight quantization (Gupta et al. 2015).

Recently, dynamic inference has emerged as a promising way to reduce the computational cost by dynamically changing the network according to each input sample (Huang et al. 2018, Gao et al. 2019). For example, we can allocate a small network for easy samples while a big network for hard ones in image classification task. The small network is enough to classify the simple samples and it has a small computational cost. The big network with more computational cost is more capable to handle difficult samples than the small network. As a result, we can reduce the computational cost of easy samples while maintaining the overall prediction accuracy at the same time.

The multi-stage network is one of the solutions to achieve dynamic inference. It has several inference stages, and each stage contains a sub-network with a prediction layer. At first, the input sample is sent to the first stage to perform the inference. If the confidence of the prediction is larger than a threshold, the inference process exits at this stage. In this paper, we use the highest value of the softmax output as the confidence. If the confidence is smaller than the threshold, the inference of the next stage should be performed until the final stage is reached.

However, design a multi-stage CNN architecture is a non-trivial task to meet the goal of maximizing prediction accuracy under the constraint of the computational cost. Different from the static network with a single stage, we need to separately design the architecture for each stage. At the same time, we are able to reuse the feature maps of previous stages by the latter stages in multi-stage network to avoid double calculate these features. Therefore, designing a network in such a huge design space is very complicated.

In recent years, neural architecture search (NAS) has made great achievements in the design of neural networks (Zoph and Le 2017, Tan and Le 2019), which can automatically searches for the optimal network architecture under certain constraints. S2DNAS (Yuan et al. 2019) first propose to use NAS to search for the multi-stage CNN architectures. It transform a static networks to multi-stage networks by dividing each layer into several stages. However, S2DNAS is largely limited to the original network architecture, which leads to a small search space and a limited performance. Meanwhile, S2DNAS has to train all of the sampled architectures during the search process, which is too inefficient to apply to large tasks such as ImageNet classification.

In this paper, we introduce a general framework, ENAS4D, which can efficiently search for optimal multi-stage CNN architecture for dynamic inference in a well-
Figure 1: Overview of ENAS4D. We can sample sub-networks from the once-for-all network to build the search space of multi-stage architectures. Efficient NAS is used to search for the optimal multi-stage architecture.

Designed search space. Firstly, we propose a method to construct the search space with multi-stage convolution. The search space includes different numbers of layers, different kernel sizes, and different numbers of channels for each stage and the resolution of input samples. The search space is significantly larger than the previous works (about $10^{37}$ in our experiments). Then, we train a once-for-all network that supports to sample diverse multi-stage CNN architectures. A specialized multi-stage network can be obtained from the once-for-all network without additional training. Finally, we devise a method to efficiently search for the optimal multi-stage network that trades the accuracy off the computational cost taking the advantage of once-for-all network. Specifically, we devise a metric that combines the accuracy and computational cost of different stages to evaluate the multi-stage architecture. Then we train an efficient metric predictor to predict the metric of a given architecture and use the evolutionary algorithm to search for the optimal multi-stage architecture. In this way, we can greatly reduce the cost of NAS.

Experiments on image classification task shows the multi-stage CNN generated by ENAS4D consistently outperforms state-of-the-art methods for dynamic inference. In particular, the network achieves 74.4% ImageNet top-1 accuracy under 185M average MACs. The time cost is about 2200 GPU hours in total and we can derive new specialized neural networks for many different constraint in minutes.

Related Work

Dynamic Inference

The idea of dynamic inference is to allocate different computation for different input samples and it is also called adaptive inference. Some of the previous works attempted to add controllers to select which computations are executed. For example, (Dong et al. 2017) skip the computation of inactive pixels in feature maps by using an extra convolution layers as the controller; (Lin et al. 2017; Gao et al. 2019; Wang et al. 2020) skip the computation of a set of channels in convolution based on the attention generated by additional linear layers or RNN; (Liu and Deng 2018; Wu et al. 2018; Veit and Belongie 2018; Wang et al. 2018) proposed to dynamically drop the whole layers or blocks; (Chen et al. 2020) dynamically aggregates multiple parallel convolution kernels based on the kernel-wise attention.

On the other hand, multi-stage networks is a feasible way to achieve dynamic inference, which contain multiple stages. The inference of input sample can exit from any stage according to the confidence for the prediction of different stages. (Panda, Sengupta, and Roy 2016; Teerapittayanon, McDaniel, and Kung 2016; Berestizhevsky and Even 2019) augment the static CNNs with additional side branch classifiers to enable dynamic inference. (Huang et al. 2018) design a novel multi-stage network architecture to reuse the feature maps of different stages by inter-connecting them with dense connectivity. (Yang et al. 2020) use the low-resolution representations for classifying easy inputs by designing the resolution adaptive networks. Recently, (Yuan et al. 2019) propose to transform a given static network to a multi-stage network to support dynamic inference by using network architecture search.

Neural Architecture Search

Neural architecture search (NAS) is to automatically design the network architecture. (Zoph and Le 2017) use reinforcement learning to sample architectures. However, the sampled network should be train from scratch and this takes too much time and the computational cost is not considered. (Pham et al. 2018; Liu, Simonyan, and Yang 2019) share the weights among different architectures to boost the search efficiency. (Tan et al. 2019; Tan and Le 2019; Cai et al. 2020) combine the accuracy of network and computational cost of the hardware into the search target.

Method

Overview of ENAS4D

The overview of ENAS4D is depicted in Figure 1. Firstly, a once-for-all network is trained. We can sample sub-networks from it with different settings, including different numbers of layers, kernel sizes, channels of intermediate feature maps and input resolution. Next, we use these sub-networks to build the multi-stage CNN that can support dynamic inference. These multi-stage CNN architectures compose the search space. Finally, an efficient NAS algorithm is used to search for the optimal multi-stage architecture.
The structure of Multi-stage CNN

Multi-stage CNN is one of the methods to achieve dynamic inference. It has \( S \) inference stages, and each stage contains a sub-network \( f_s \) with a prediction layer. An input sample \( x \) is sent to the network to perform the inference stage by stage. The confidence of the prediction of the stage \( s \) is larger than a threshold \( T_s \), the inference process exits at this stage. Otherwise, the inference of the next stage should be performed until the final stage is reached.

In this way, it can dynamically change the computation cost for different input samples. When designing the multi-stage CNN architectures, we can use different network architectures for each sub-network to maximize the predictive performance of different stages. Moreover, we can reuse the feature maps generated by the previous stage in the later stages, thereby further reducing the computation cost of the sub-network in the later stages.

In the following part, we will introduce the basic component called multi-stage convolution, then how to use it to build multi-stage residual block and multi-stage network.

Multi-stage Convolution The convolution layer is the most important component of CNN. It processes \( C \) input feature maps \( X = \{X_1, X_2, \ldots, X_C\} \) and outputs \( O \) output feature maps \( Y = \{Y_1, Y_2, \ldots, Y_O\} \) with weight \( W \in \mathbb{R}^{O \times C \times K \times K} \), where \( K \) is the kernel size. The typical convolution is formulated as:

\[
Y_j = \sum_{i=1}^{C} \text{CONV}(W_{ji}, X_i),
\]

where the \( \text{CONV} \) is the basic convolution operation on a input channel using a convolution filter.

In order to support dynamic inference, we design three types of multi-stage convolution, namely independent, input reuse and output reuse. The first type is called independent that is to use \( S \) independent convolutions as shown in Figure 2(a). For the input of each stage, the weight of the corresponding stage is selected for convolution operation, which is formulated as:

\[
Y_j^s = \sum_{i=1}^{C_s} \text{CONV}(W_{ji}^s, X_i^s),
\]

where the \( Y^s \) is the output of stage \( s \), the \( X^s \) is the input of stage \( s \), the \( W^s \) is the weight of convolution in stage \( s \) and \( C_s \) is the number of input channels of stage \( s \). We can choose different numbers of output channels and different kernel sizes for different stages for this type of multi-stage convolution.

The second is input reuse, which is shown in Figure 2(b). In order to reuse the input feature maps of the previous stage, we concatenate them with the input of the current stage as the input of the convolution, which is formulated as:

\[
Y_j^s = \sum_{k=1}^{C_s} \sum_{i=1}^{C_s} \text{CONV}(W_{ji}^s, X_i^s),
\]

where the \( W^s \) is the part of weight for \( X^s \).

The third type is called output reuse and it is shown in Figure 2(c). The output of the convolution in each stage will be element-wisely added to the result of the previous stage. In order to use this type of multi-stage convolution, the number of output channels by all stages needs to be the same. This type of multi-stage convolution is formulated as:

\[
Y_j^s = \sum_{i=1}^{C_s} \text{CONV}(W_{ji}^s, X_i^s) + Y_j^{s-1}.
\]

Multi-stage Residual Block The residual block is proposed in (He et al., 2016), which is widely used in a lot of CNN architectures. A residual block contains several convolution layers which process the input feature maps and a residual connection is used to add up the input and convolution output. We designed a method to build the multi-stage residual block using the multi-stage convolution. As demonstrated in Figure 3, the first convolution layer of the residual block uses independent type and the last convolution uses output reuse type, which ensures the channels of input feature maps and that of the output feature maps is consistent at each stage. We can assign different types for the other convolution layers in different residual blocks. For example, input reuse type is used for the second layer in the figure, and independent type is used for the depth-wise convolution in our experiment.
Multi-stage Network  
Next, we introduce how to build a multi-stage network by using multi-stage convolution and multi-stage block. As shown in the Figure 4, the network contains a multi-stage convolution of independent type as the first layer and three multi-stage residual blocks. The prediction layer is added to the end of each stage. Note that we can skip the computation of some layers in some stages, as an example, the third block skips the second stage in the figure. In this way, we can set different numbers of layers for different stages of the network.

Sample Multi-stage CNN from Once-for-all Network

An once-for-all network consists a few of convolution layers and residual block groups. A residual group contains $N$ residual blocks and each residual blocks contains several convolution layers. Some of the convolution layers can be stride of 2 to reduce the resolution of the feature map. Our goal is to sample different multi-stage CNN architectures from the once-for-all network, including different number of layers or blocks in each stage, different kernel size in each layer, different number of channels in each stage, and different input image resolution. Next, we will introduce how to sample with different configurations.

Sample multi-stage width  
Width means the number of channels. For single convolution layer, we first sort the channels based on the L1 norm of weight in once-for-all network. In order to generate $\{C_1, C_2, \ldots, C_S\}$ number of channels for $S$ stages for independent type and input reuse type, we assign the most important $C_1$ channels to stage 1, next $C_2$ channels to stage 2 and so on. Thereby, the earlier stages use the more important channels to ensure accuracy. For the output reuse type, we use all of the output channels of the layer in each stage. The weight is initialized as the weight for corresponding input and output channels. For residual blocks, since the output reuse type is used for the last convolution, we should sample the channels in each stage for the intermediate layers.

Sample multi-stage kernel size  
The same as (Cai et al. 2020), we use the center of a 7x7 convolution kernel in once-for-all network to multiply with a transformation matrix to get the 5x5 kernel and the center of the 5x5 kernel to multiply with another transformation matrix to get the 3x3 kernel. We sample different kernel sizes for different multi-stage convolution layers and initialize them with the weight after transformation in the corresponding location.

Sample multi-stage depth  
In order to generate $\{D_1, D_2, \ldots, D_S\}$ numbers of blocks for $S$ stages in a block group, we keep the first $D_s$ blocks in stage $s$. The stage $s$ skip the computation of the last $N - D_s$ blocks. If the stage $s$ is skipped, the next stages $s + 1$ need to calculate the channels of the stage $s$ to ensure important channels are not skipped. $D_s$ is sampled from a depth pool and we constraint $D_i \leq D_j$ when $i < j$.

Sample the resolution of input image  
In order to keep the resolution of input feature maps in each stage equal to the resolution of the reused feature maps, we share the resolution of input image $R$ at each stage. The resolution is sampled from a image resolution pool.
Training the Once-for-all Network

We sample multi-stage sub-networks to train at each training iteration. Specifically, after a multi-stage sub-network is sampled, inference is performed for each stage and the output of the prediction layer in each stage is got. Then, we calculate the loss for each stage separately, and sum these losses to get the total loss. Finally, we perform back propagation with the total loss and update the weight. In order to improve the performance, knowledge distillation is used for the loss at each stage to mimic the output of complete once-for-all network.

Efficient Network Architecture Search

After training of the once-for-all network, NAS is used to search for the optimal multi-stage architecture with high accuracy and low computational cost. Firstly, we devise a evaluation metric \( R \) combining the accuracy and calculation cost of different stages to evaluate the multi-stage architecture. Then, we train an metric predictor to predict the metric of a model given its architecture and input image size. Finally, we use the evolutionary algorithm to search for the optimal multi-stage architecture.

Evaluation metric

A dataset \( D \) is used to evaluate the metric on a multi-stage CNN. Using dynamic inference, each input sample in a dataset \( D \) exit from different stages, and we count the number of samples exit from each stage (notated as \( N_s \)) and the prediction accuracy of each stage (notated as \( ACC_s \)). We can also count the accumulative computational cost (MACs or latency on specific device) of the inference exit from each stage (notated as \( COST_s \)). Then we calculate the average accuracy and the average computational cost over the dataset:

\[
\text{ACC}_{\text{avg}} = \frac{1}{|D|} \sum_{s=1}^{S} ACC_s \times N_s,
\]

\[
\text{COST}_{\text{avg}} = \frac{1}{|D|} \sum_{s=1}^{S} COST_s \times N_s,
\]

where \( |D| \) is the number of samples in the dataset. Then we define the metric \( R \) by combining them:

\[
R = \text{ACC}_{\text{avg}} \times (\text{MIN}(\frac{\text{COST}_{\text{target}}}{\text{COST}_{\text{avg}}}, 1))^{\omega},
\]

where \( \text{COST}_{\text{target}} \) is the target cost and the factor \( \omega \) is used to adjust the relative importance between accuracy and computational cost.

Grid search for threshold

Firstly, we set the threshold of each stage to 1. Then, the multi-stage network inference the samples in \( D \) without early exiting. We obtain the prediction confidence and correctness of each sample in each stage, and record them in a database. At last, given \( \omega \) and \( \text{COST}_{\text{target}} \), the grid search is used to search for thresholds for all stages to maximize the evaluation metric. The time cost of grid search is negligible (about 200ms in our experiment). Therefore, after the confidence and accuracy database is established, we can quickly set thresholds for different \( \omega \) \( \text{COST}_{\text{target}} \).

Metric predictor

Since it takes a long time to evaluate a network using the test dataset, we train a metric predictor which is a multi-layer perceptron to predict the metric of a model given its architecture and input image size. Firstly, we randomly sample 18K multi-stage sub-networks with different architectures and input image sizes, then evaluate the metric on 10K images which is sampled from the training dataset. Then, we encode the architecture settings into the a feature vector by concatenate the one-hot vector of widths, kernel sizes, depths and input resolution. At last, we train the predictor given the feature vector as input and the metric as target.

Search with evolutionary algorithm

We can quickly generate multi-stage architectures and test the predicted the metric using trained metric predictor. Evolutionary algorithm (Real et al. 2019) is used to search the optimal multi-stage architecture. In our experiment, the search process takes only several minutes.

Experiments

To verify the effectiveness of ENAS4D, we search for the optimal multi-stage CNN architecture on the ImageNet classification task. ImageNet (Deng et al. 2009) contains 1,281,167 samples of 1,000 classes for training and 50,000 samples for validation. We use the original validation set for testing and sample 10,000 images from training set for evaluating the metric and setting the thresholds. We also evaluate different aspects of the searched network, which are presented in the discussion part.

Experiment Settings

Model setup

In our experiments, we use the same once-for-all network in (Cai et al. 2020). We initialize the network with the pre-trained weight. The metric predictor is a 3-layer perceptron that has 400 hidden units in each layer.

Sample settings

The number of stages \( S \) is set to 3, the input resolution pool of the network is set to [128, 144, 160, 176, 192, 208, 224], the depth pool of the block group is set to [2, 3, 4], the kernel size pool of the depth-wise convolution is set to [3, 5, 7]. In each residual block, the cumulative ratio of the number of intermediate channels can be select form \([1/2, 2/3, 1]\).

Training details

We use the standard SGD optimizer with Nesterov momentum 0.9 and weight decay 3e-5. The initial learning ratio is set to 4.5e-3 and we use cosine schedule for learning rate decay. The fine-tune from pre-trained network takes 24 epochs with batch size 192 on 3 GPUs. The training takes about 90 GPU hours. We set \( \omega \) to 0.09 for evaluation metric. And we use the Adam optimizer for the training of metric predictor for 30 epochs. We use the RMSE between the predicted metric and estimated metric as the loss. The learning rate is set to 1e-4 and the weight decay is set to 1e-5.

Search Results on ImageNet

Searched networks under different cost target

We set the target computation cost to 90M MACs (ENAS4D-A),
Table 1: Evaluations on the searched multi-stage CNN architectures for dynamic inference. The average top-1 accuracy on ImageNet, average computational cost in MACs and the cumulative computational cost for each stage are reported.

| Network | Average top-1 | Average MACs | Cumulative MACs |
|---------|---------------|--------------|-----------------|
| A       | 70.5          | 92           | 75, 148, 240    |
| B       | 70.8          | 123          | 90, 175, 218    |
| C       | 72.1          | 153          | 103, 149, 237   |
| D       | 74.4          | 185          | 141, 201, 359   |

Figure 5: Comparing ENAS4D with other methods for dynamic inference. We plot the points of (the average computation cost, the average top-1 accuracy) on test set of ImageNet.

120M MACs (ENAS4D-B), 150M MACs (ENAS4D-C) and 180M MACs (ENAS4D-D) in evaluation metric, and perform the architecture search to get the multi-stage CNNs. Table 1 reports the performance of the searched multi-stage networks using ENAS4D. With different COST target, ENAS4D is able to sample a suitable multi-stage CNN architecture from once-for-all network. The cumulative MAC of the network increases as the stage increases. The computation costs of the stage are much smaller than that of the third stage and that of the second stage is near the average of the first and third stages. This shows that ENAS4D can select the proper sub-network for different stages, so that each stage can extract a reasonable number of features to process samples of different difficulty. The detailed analysis for different stages is located at the discussion part.

Comparing with other methods for dynamic inference

Figure 5 comparing the performance of the multi-stage CNNs generated with ENAS4D with other methods for dynamic inference, including RANet (Yang et al. 2020), MSDNet (Huang et al. 2018), SkipNet (Wang et al. 2018) and FBS (Gao et al. 2019). The networks search by ENAS4D are substantially more accurate than other networks for dynamic inference with the same amount of computation cost.

Table 2: Time cost for each step. The data of pre-train once-for-all network is from (Cai et al. 2020).

| Step                        | Reusable | Cost         |
|-----------------------------|----------|--------------|
| Pre-train once-for-all network |         | 2000 GPU hours|
| Train for dynamic inference | ✓        | 90 GPU hours  |
| Build the confidence and correctness database | ✓        | 100 GPU hours  |
| Train metric predictor      |          | < 10 min     |
| Evolutionary search         |          | < 3 min      |

Time cost

Table 2 demonstrates the time cost of each step of ENAS4D. Training once-for-all for dynamic inference from scratch takes about 2090 GPU hours, which only needs to be executed once. The testing of the confidence and correctness for the 18K sampled multi-stage CNNs takes 100 GPU hours. Since we store the results in the database, this time-consuming testing also needs to be executed once. Comparing to the previous steps, the time for training of metric predictor and evolutionary searching is negligible. We can efficiently search for different multi-stage CNN architectures under different constraint of computation cost.

Discussion

Table 3: Top-1 accuracy and fractions of samples in test set of ImageNet that exit from each stage.

| Network | A | B | C | D |
|---------|---|---|---|---|
| Stage 1 | 79.4% | 85.7% | 94.6% | 89.5% |
| Fractions | 80.3% | 67.2% | 44.3% | 64.7% |
| Stage 2 | 37.1% | 49.3% | 70.5% | 57.1% |
| Fractions | 17.3% | 21.6% | 27.9% | 20.9% |
| Stage 3 | 15.6% | 23.1% | 38.2% | 31.8% |
| Fractions | 2.3% | 11.2% | 27.9% | 14.4% |

Difficulty distribution of test dataset

In Table 3, we give the statistics of all the samples in the test set of ImageNet. We observed that more than 60% of the samples are exit form the first two stages, which means most of the images are simple samples. The accuracy of the first stage is much higher than the later stages, which indicates that the small networks in early stage can easily classify those samples.

Visualization

Figure 5 illustrates the samples exit from different stages the test set of ImageNet. We can see from the figure that the sample exit from different stages have different recognition difficulties. With the rise of the stage, the difficulty of recognition is also rising, which also validates the intuition that easy samples can be classified using fewer computations.
Figure 6: Visualization of ImageNet samples exit from different stages.

Table 4: Evaluations on the searched multi-stage CNN architectures for dynamic inference. The average top-1 accuracy on ImageNet and average latency on the desktop and the GPU server.

| Platform | Target latency | Average top-1 | Average latency |
|----------|----------------|---------------|----------------|
| Desktop  | 10ms           | 74.2          | 9.8ms          |
|          | 8ms            | 72.9          | 8.0ms          |
|          | 6ms            | 72.2          | 6.4ms          |
| GPU      | 30ms           | 74.2          | 30.2ms         |
| Server   | 25ms           | 73.3          | 25.4ms         |
|          | 20ms           | 72.8          | 20.6ms         |

**Deploy on real-world devices** In real-world deployment, multi-stage CNNs needs to run on specific hardware. However, the computational efficiency of each type of hardware for different network architecture is different. So we should search for the optimal multi-stage CNN architecture for each specific hardware. Therefore, it is necessary to change the $COST_{\text{avg}}$ and $COST_{\text{target}}$ from MACs to latency on specific hardware. Since we have established a database of prediction confidence and correctness before, we can quickly generate data and train a new metric predictor. We chose a desktop (Intel 17-6700K) and a GPU server (Nvidia GTX 1080ti) for experimentation. We first build a database for the hardware latency of operations under different input conditions. We only need to look up the table to get the latency of different stages of a multi-stage architecture. Table 4 demonstrates the result on the desktop and the GPU server.

The inference of the generated multi-stage CNNs does not introduce irregular computations or complex controllers. Thus the generated model can be easily deployed on various hardware devices using existing deep learning frameworks. Moreover, our method is orthogonal to quantization methods, which can further reduce the computational cost of the multi-stage CNNs. All these properties of our method imply a wide range of application scenarios where the efficient CNN inference is desired.

**Conclusion**

In this paper, we present a general framework called ENAS4D, for efficiently search for the multi-stage CNN architectures for dynamic inference. In contrast to previous methods, our method comes with three advantages: (1) Our method can simultaneously search for different architecture for different stages. (2) Our method generate a large search space including numbers of layers, kernel sizes, numbers of channels and resolution of input image. (3) Our method has high search efficiency by using the technique of once-for-all. The experiments on ImageNet classification benchmark demonstrate the effectiveness of the proposed method. The generated multi-stage CNN architecture can consistently outperform the previous methods for dynamic inference.

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