IA-RED$^2$: Interpretability-Aware Redundancy Reduction for Vision Transformers

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Abstract

The self-attention-based model, transformer, is recently becoming the leading backbone in the field of computer vision. In spite of the impressive success made by transformers in a variety of vision tasks, it still suffers from heavy computation and intensive memory costs. To address this limitation, this paper presents an Interpretability-Aware REDundancy REDuction framework (IA-RED$^2$). We start by observing a large amount of redundant computation, mainly spent on uncorrelated input patches, and then introduce an interpretable module to dynamically and gracefully drop these redundant patches. This novel framework is then extended to a hierarchical structure, where uncorrelated tokens at different stages are gradually removed, resulting in a considerable shrinkage of computational cost. We include extensive experiments on both image and video tasks, where our method could deliver up to $1.4 \times$ speed-up for state-of-the-art models like DeiT$^5$ and TimeSformer$^5$, by only sacrificing less than 0.7% accuracy. More importantly, contrary to other acceleration approaches, our method is inherently interpretable with substantial visual evidence, making vision transformer closer to a more human-understandable architecture while being lighter. We demonstrate that the interpretability that naturally emerged in our framework can outperform the raw attention learned by the original visual transformer, as well as those generated by off-the-shelf interpretation methods, with both qualitative and quantitative results. Project Page: [http://people.csail.mit.edu/bpan/ia-red/](http://people.csail.mit.edu/bpan/ia-red/)

1 Introduction

Transformer, a self-attention-based architecture processing sequential input without any recurrent or convolutional operations, has set off a storm in the computer vision literature recently. By dividing the input image into a series of patches and then tokenizing them with linear transformation, the transformer can effectively process the visual data in different modalities$^{[13, 53, 54, 28, 3, 17, 66]}$. Despite its versatility, the transformer is always deeply troubled with inefficient computation and its vague interpretability. The vision transformer suffers heavy computational costs, especially when the input sequence is long. As the attention module in the vision transformer computes the fully-connected relations among all of the input patches, the computational cost is then quadratic with regard to the length of the input sequence. On the other hand, previous works$^{[6, 8]}$ have already shown the vulnerable interpretability of the original vision transformer, where the raw attention comes from the architecture sometimes fails to perceive the informative region of the input images.

Recently, more designs of vision transformer architecture$^{[14, 65, 18, 56, 14, 9, 3]}$ are proposed to get higher accuracy with less computational cost. Although these methods anchor good trade-offs between efficiency and accuracy, their compression makes the vision transformer even more lack interpretability. Most of these methods assume that the input sequences are sampled from a regular visual input in a fixed shape rule, and thus their network architectures are not flexible as well, which makes the vision transformer (1) no longer able to process the input sequence with arbitrary length as the architecture is designed for a specific input shape; (2) neither model-agnostic nor task agnostic anymore; or (3) neglect the fact that the model redundancy is also input-dependant. We yet argue that

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there is no inherent tension between efficiency and interpretability, and achieving them both does not have to pay design flexibility as a price. Indeed, starting from the philosophy of Occam’s razor, the law of parsimony, or always pursuing more compact solutions when possible, is always treated as a rule-of-thumb for pursing interpretability, especially in complicated fitting problems [21].

This paper aims to seek the win-win between efficiency and interpretability while keeping the flexibility and versatility of the original vision transformer. We propose a novel Interpretability-Aware REDundancy REDuction (IA-RED$^2$) framework for reducing the redundancy of vision transformers.

The key mechanism that IA-RED$^2$ uses to increase efficiency is to dynamically drop some less informative patches in the original input sequence so that the length of the input sequence could be reduced. While the original vision transformer tokenizes all of the input patches, it neglects the fact that some of the input patches are redundant and such redundancy is input-dependant (see from Figure 1). As the computational complexity of the attention module is quadratically linear to the input sequence length, the effect of reducing input sequence length would be magnified in the amount of the computation. Motivated by this, we leverage the idea of dynamic inference [39, 37, 38, 61, 57], and adopt a policy network (referred to as multi-head interpreter) to decide which patches are uninformative and then discard them. Our proposed method is inherently interpretability-aware as the policy network learns to discriminate which region is crucial for the final prediction results.

To summarize, the main contributions of our work includes: (1) We propose IA-RED$^2$, the first interpretability-aware redundancy reduction framework for vision transformer. (2) Our IA-RED$^2$ framework is one of the first input-dependent dynamic inference framework for vision transformer, which adaptively decides the patch tokens to compute per input instance. (3) IA-RED$^2$ is both model-agnostic and task-agnostic. We conduct experiments with IA-RED$^2$ framework spanning different tasks, including image recognition and action recognition, and different models, including DeiT [53], TimeSformer [3]. (4) We attain promising interpretable results (shown in Figure 3) over baselines, with a 1.4× acceleration over DeiT on image recognition tasks, and a 4× acceleration over TimeSformer on video action recognition task while largely maintaining the accuracy. We also provide both qualitative results regarding interpretability with heatmaps by our method and those from other baseline methods like raw attention, MemNet [29]; as well as the quantitative comparison with current state-of-the-art model interpretability methods, such as GradCAM [44], on ImageNet-Segmentation [16] dataset with the weakly-supervised image segmentation task.

2 Related Work

Interpretability of Neural Networks. Besides improving the discrimination power of deep neural networks, model interpretability has recently raised another significant and popular research question. One of the important goals is to predict the heatmap visualization that precisely indicates the objects or contexts of relevance. Simonyan et. al. [45] attempts to maximize the class score that generates a saliency map for the given inputs. Dabkowski et al. [12] mask the salient parts of the inputs to manipulate the scores of the classifier, which generalizes well to unseen images and enables fast saliency detection. Khosla et al. [29] provide the largest annotated image memorability dataset to benchmark the visualization and explanation of natural images. After that, gradient-based methods [49, 46, 47] are proposed to generate precise heatmaps, by computing the gradient with respect to input during the backpropagation. While all the above approaches are studying the interpretability of convolutional neural networks (CNNs), only a few works contribute to the visualization of the vision transformer. Chefer et al. shed some light on its visualization by assigning the local relevance on Transformer layers. Caron et al. [6] demonstrate that a self-supervised trained ViT produces explicit representation about the semantic location of a given object in natural images. Different from all of them, our approach starts with a novel multi-head interpreter which is supervised
by an efficiency-driven signal, and then benefits from this powerful interpreter by reducing the redundancy of transformer, achieving a “win-win” between interpretability and efficiency.

**Dynamic Networks.** Neural networks are found as redundant regarding their huge computation cost [19] 23, 35. To overcome this issue, many adaptive computation methods are explored during the inference stage [11,2,57,15,26,58,20]. These adaptive computation strategies help speed up the inference time of convolutional neural networks (CNNs) 35, recurrent neural network (RNNs) 15, and also self-attention based methods (BERT) 25. Besides the model-level adaptation, others further extend this idea to data-level adaptation, by either reducing the spatial redundancy 63 or focusing on key area 59. However, those methods are limited by the convolutional structure, where only 2D data can be taken as input. Different from those approaches, our methods naturally benefit from the unstructured input taken by vision transformer, and thus can provide a much more precise glance at the target object with the affection of background being eliminated.

**Vision Transformer.** Transformer, as a self-attention based model, has been widely adopted in natural language processing area before. The recent advance [13] shows that the transformer can also achieve incredible performance on computer vision tasks. While vision transformer suffers from the necessity large-scaled dataset 48, many recent works try to encode strong inductive prior by either combining it with convolutional layer 60, 32, 64, 62 or introducing 2D-hierarchical structure to vision transformer 34, 56, 14, 9. Besides, transformer also shows strong power in other vision tasks, including semantic segmentation 67, object detection 5, 68, image processing 10, and image generation 28, 27. These successes further suggest the potential of transformer to become the universal model for general vision tasks. Some other works 40, 11, 51 also make meaningful efforts on vision transformer efficiency. Different from those methods, the proposed method achieves a “win-win” on both efficiency and interpretability.

## 3 Proposed Method

Our main goal is to reduce the redundancy in vision transformers by dynamically dropping less informative patches in the original input sequence while classifying it correctly with the minimum computation. Our method is built on top of vision transformer (ViT) [13]. We start from presenting a brief overview of ViT, including the computational complexity of each module regarding the input sequence length. We then describe our proposed IA-RED framework for hierarchically reducing the redundant patch tokens at different layers of the vision transformer.

### 3.1 Overview of Vision Transformer

Vision transformer mainly consists of three main modules: (1) Multi-head Self Attention layer (MSA) to learn relationships between every two different patches among all the input tokens. There are $h$ self-attention heads inside the MSA. In each self-attention head, the input token $X_i$ is first projected to a query $Q_i$, a key $K_i$, and a value $V_i$ by three different linear transformations. Then, the query $Q_i$ computes the dot products with all the keys $K_i$ and these dot products will be scaled and normalized by the softmax layer to get the attention weights. After that, it outputs the token $Y_i$ by weighted sum up all the values $V$ with the obtained attention weights. Finally, the outputs from all heads are concatenated and re-projected by a linear layer into an output token. (2) Feed-Forward Network (FFN) which consists of two linear layers which are connected by the GeLU activation function. For each output token $Y_i \in \mathbb{R}^D$ from the precedent MSA layer, FFN processes it individually. The first linear layer upgrades its dimension from $D$ to $4D$, and the second linear layer downgrades its dimension from $4D$ to $D$. Both MSA and FFN are functioning as residual connection [22]. (3) Linear Patch Embedding and Positional Encoding: For an image or a video clip, ViT first splits it into several fixed-size patches and embeds them into input tokens with a linear layer. After transforming the original image and video into a series of tokens, the network is no longer capable of being aware of the positional information of the input tokens. Thus the positional embeddings are added to the input tokens right after the patch embedding to learn the positional information of each token.

**Computational Complexity.** For an input sequence $N \times D$, where $N$ is the length of the input sequence and $D$ is the embedding dimension of each input token. The computation complexity of the MSA is $O(4ND^2 + 2N^2D)$. While for the FFN, the computational complexity is $O(8ND^2)$. As the computational complexity of patch embedding can be neglected compared with the MSA and FFN, the total computational complexity of the ViT is $O(12ND^2 + 2N^2D)$. 

3
Figure 2: Illustration of our proposed IA-RED² framework. We divide the transformer into $D$ groups. Each group contains a multi-head interpreter and $L$ combinations of the MSA and FFN. Before input to the MSA and FFN, the patch tokens will be evaluated by the multi-head interpreter to drop some uninformative patches. The multi-head interpreters are optimized by reward considering both the efficiency and accuracy. Best viewed in color.

3.2 Interpretability-Aware Redundancy Reduction

In this section, we introduce our multi-head interpreter in detail which uses a policy token to estimate the importance of the input token. We also demonstrate how we hierarchically train the multi-head interpreter based on a pre-trained vision transformer. Finally, we illustrate that how the interpretability emerges in our IA-RED² framework.

Multi-head Interpreter. We borrow the idea from the architecture of the MSA layer to devise our policy module, named multi-head interpreter. Given a sequence of patch tokens $X \in \mathbb{R}^{N \times d}$ which already contain the positional information, we drop the uninformative patch tokens by using the multi-head interpreter. We first divide the original ViT evenly into $D$ groups, each group contains a multi-head interpreter and $L$ blocks which consists of one MSA layer and one FFN. Inside each group, before inputting to the blocks, the patch tokens will first be evaluated by the multi-head interpreter for the informative score $I_{ij}$, where $i$ and $j$ represent the position of the input token and the group respectively. If $I_{ij}$ is below the threshold 0.5, the patch $X_i$ will be completely discarded at $j^{th}$ group and will not be available in the subsequent groups. The $I_{ij}$ is obtained by:

$$I_{ij} = \frac{1}{H} \sum_{h} \phi(F_h^b(X_i) \ast F_h^p(P_j)),$$  

where $P_j$ is the policy token in the $j^{th}$ multi-head interpreter, $H$ is the number of the heads in the multi-head interpreter, $F_h^b$ and $F_h^p$ are the linear layer at $h^{th}$ head for the patch tokens and the policy token respectively, $\ast$ represents the dot product and $\phi$ the sigmoid activation function.

Hierarchical Training Scheme. Our hierarchical training scheme is built on top of a well-trained ViT. In our IA-RED² framework, all of the MSA-FFN blocks in the original vision transformer will be evenly assigned into $D$ groups in our IA-RED² framework, where each group contains $L$ MSA-FFN blocks and one multi-head interpreter. We fix the parameters of the patch embedding layer, positional encoding, and the class token during the training, and only focus on the parameters inside each group. The network groups are optimized in a curriculum learning manner. For example, if the number of groups $D$ is 3, we will first optimize groups 1 to 3, then 2 to 3, and finally, we optimize the third group. Intuitively, we hope the interpreter at the early stage could learn to select the patches containing all of the necessary contextual information for the correct final prediction, while the interpreter at later stages could focus more on the part-level information since now each token’s information has already gone through global interaction and fusion. The pseudo-code for the above optimization pipeline can be referred in supplementary materials. We optimize the multi-head interpreters by using the REINFORCE method where the reward considers both the efficiency and accuracy, and finetune the MSA-FFN blocks with gradients computed based on cross-entropy loss.
Formally, during the training phase, given a sequence of patch tokens $X \in R^{N \times d}$ input to the $j^{th}$ multi-head interpreter, the multi-head interpreter will generate policies for each input token of dropping or keeping it as Bernoulli distribution: $\pi_W(u_i|X_i) = F_{ij}^u \times (1 - I_{ij})^{1-u_i}$, where $u_i = 1$ means to keep the token and $u_i = 0$ means to discard the token. $I_{ij}$ is defined in the Eq. [3] and $X_i$ denotes the $i^{th}$ token in the token sequence $X$. We associate these actions with the reward function:

$$R(u) = \begin{cases} 1 - \left( \frac{|u|_0}{N} \right)^2 & \text{if correct} \\ -\tau & \text{otherwise} \end{cases}, \quad (2)$$

where $\left( \frac{|u|_0}{N} \right)^2$ measures the percentage of the patches kept, and $\tau$ is the value of penalty for the error prediction which controls the trade-off between the efficiency and the accuracy of the network. This reward function encourages the multi-head interpreter to predict the correct results with as few patch tokens as possible. Then we optimize the multi-head interpreter individually by the expected gradient:

$$\nabla_{W_j} J = E_{u \sim \pi}[A \nabla_{W_j} \sum_{i=1}^{N} \log[I_{ij}u_i + (1 - I_{ij})(1 - u_i)]], \quad A = R(u) - R(\hat{u}), \quad (3)$$

where $J = E_{u \sim \pi}[R(u)]$ is the expected reward to compute the policy gradient [50], $W_j$ denotes the parameters of the $j^{th}$ multi-head interpreter. We use the self-critical baseline $R(\hat{u})$ in [41] to reduce the variance of optimization, where $\hat{u}$ denotes the maximally probable configuration under the current policy: i.e., $u_i = 1$ if $I_{ij} > 0.5$, and $u_i = 0$ otherwise. As the computation of the $j^{th}$ multi-head interpreter is based on the output tokens of $(j-1)^{th}$ group, we optimize the entire network in a curriculum learning manner. We first train the interpreter in the earlier layer, and then fix the interpreter and finetune all of the subsequent MSA-FFN blocks. Let’s take the $j^{th}$ group for example. For the first $j$ group, we first only train the multi-head interpreter and then fix it while optimizing the subsequent MSA-FFN modules in the $j^{th}$, ..., $D^{th}$ groups. When we optimize the $j^{th}$ group, the multi-head interpreter in the latter groups will be masked and keep all of the tokens.

**Emergence of Interpretability.** By visualizing the informative scores predicted by the multi-head interpreters in different network groups, we can see the redundancy of the input patches is hierarchically reduced at different levels clearly. For those patches that are removed in the precedent groups, we treat the informative score of them as zero. Thus we can obtain a sequence of the informative scores from each network group whose length equals the original input sequence length. We rearrange this score sequence and interpolate it back to the size of the input vision content (e.g. image or video). As the range of the informative score is from 0 to 1, we can draw a heatmap for each network group which interprets that what is redundant for this network group.

### 4 Experiments

**Datasets and Metrics.** We conduct image recognition experiments on the ImageNet-1k classification dataset [31]. The performance of our models on ImageNet-1k is measured with the metrics of top-1 and top-5 accuracy rates. For weakly-supervised image segmentation experiments, we adopt the ImageNet-Segmentation dataset [16] to evaluate the heatmaps we generate. We report three metrics: pixel accuracy, mean accuracy (mAcc), and mean IoU (mIoU) to reflect the segmentation performance. Finally, for video action recognition, we conduct our experiments on Kinetics-400 dataset [7], which contains 240k training videos and 10K videos for testing across 400 classes. We report the metrics of clip-1 and video-1 error of video models, which denotes the error rate of evaluating the model with the single clip and the Left-Center-Right three clips, respectively.

**Model Architectures.** We build our image model on top of DeiT [53] which adopts the architecture of the ViT [13] by modifying the depth and width. Compared to the original ViT [13], DeiT has a distillation token that is in charge of distilling the knowledge from the teacher CNN network. DeiT is trained and evaluated on ImageNet-1k [31], without large-scale pre-training. We choose DeiT-S and DeiT-B as our base models, where DeiT-B is 4× larger than DeiT-S in terms of FLOPs. For the video model, we construct our model based on TimeSformer [3]. There are several different attention mechanisms introduced in [3]. Here we adopt the TimeSformer with the JointST attention method, which keeps the architecture of the vanilla ViT and takes all of the input patches as one sequence. Our model samples 8 frames in one video clip and splits them into 1568 frame patches. During inference, our model evenly crops 3 views from the video clip, each view of them has 8 frames.
Figure 3: We visualize the heatmaps which highlight the informative region of the input images of MemNet, raw attention at the second block, and our method with DeiT-S model. We find that our method can obviously better interpret the part-level stuff of the objects of interest. Here the visualization results are randomly chosen. Best viewed in color.

Table 1: Results of weakly-supervised image segmentation on ImageNet-segmentation [16]. We use our method based on the training with DeiT-S model. Higher is better.

| Metrics   | raw attention | LIME [42] | MemNet [29] | GradCAM [44] | LRP [4] | Ours   |
|-----------|---------------|-----------|-------------|---------------|---------|--------|
| pixel accuracy | 67.87         | 67.32   | 52.81       | 65.91         | 50.72   | 70.36  |
| mAcc      | 61.77         | 47.80    | 53.70       | 55.04         | 50.62   | 64.86  |
| mIoU      | 46.37         | 33.94    | 34.66       | 41.31         | 32.62   | 49.42  |

Implementation Details. For the image recognition task, we divide the vision transformer backbone [53] into 3 ($D = 3$) groups, where each group contains 4 ($L = 4$) MSA-FFN modules and one multi-head interpreter. We optimize the entire framework for $D \times 30$ epochs. During every 30 epochs, we optimize the multi-head interpreter for 10 epochs and all of the subsequent MSA-FFN modules for 20 epochs. We use a mini-batch size of 32 images per GPU and adopt Adam [30] optimizer with an initial learning rate of 4e-5, which decays by cosine strategy [36] to train all our models. For the video understanding task, we set $D = 1$, i.e., we only select the informative patches at the input level. And we train the multi-head interpreter for 5 epochs and then finetune the backbone network for 1 epoch, mainly following the settings listed in the original paper [3]. We use a mini-batch size of 8.
Table 2: Redundancy reduction results of our IA-RED² with DeiT on ImageNet-1k [31].

| Arch. | Method | speed (fps) | Top-1 | Top-5 |
|-------|--------|-------------|-------|-------|
| original | ≤930  | 79.8 | 95.0 |
| random | ≥1360 | 78.4 | 94.2 |
| DeiT-S MemNet | ≤350 | 77.6 | 93.6 |
| attention | ≥1360 | 78.4 | 94.1 |
| ours | ≥1360 | 79.1 | 94.5 |
| DeiT-B MemNet | ≤190 | 79.9 | 94.5 |
| attention | ≥440 | 80.6 | 94.8 |
| ours | ≥440 | 80.9 | 95.0 |

视频剪辑每GPU并采用SGD优化器与初始学习率2.5e-3的余弦策略 [36]。我们使用16 NVIDIA Tesla V100-32GB GPU训练大多数模型。

4.1 Emergence of Interpretability

在这个部分，我们证明了在我们提出的模型中出现的可解释性。我们首先展示了一些定性结果，以证明我们的方法可以更好地解释正确的预测来自哪个区域。然后，我们给出了我们弱监督图像分割实验的定量结果，证明了我们的方法可以更好地在输入图像上局部化重要的对象。

Qualitative Evaluation. 我们可视化了第二网络组中多头解释器的输出，选择DeiT-S模型作为测试床。然后，我们将方法与另外两个基线进行比较：（1）Memorability map，由MemNet [29]生成，表示图像中某个区域的可记忆性，带有具体的分数范围从零到一。直观地说，可记忆性映射突显了刺激我们大脑更强烈的部分。映射中的注意力映射突显了注意力权重更重要的区域。我们通过平均CLS token和其它patch token在Block_1中的注意力权重，类似于图1中的过程。我们展示了我们的方法与两个基线的比较，我们可以看到我们的方法在感兴趣对象上更准确地局部化，特别是在层次化的部分级内容，更准确。从第三列的第二行的示例中，我们可以看到我们生成的热图与我们的方法结合的模式，可记忆性映射检测了卡车的车头，而注意力映射突显了更不相关区域，如天空中的云。在第六行的第一列中，我们的方法准确地局部化了鳍和头，鲨鱼的两个最相关信息特征，这表明我们的方法可以更好地局部化部分级内容，与原注意力相比。此外，例如，第七和第八行的示例表明我们的方法可以检测动物面部的特征，如眼睛、鼻子和耳朵。

Weakly-supervised Image Segmentation. 为了定量比较我们的方法与其他模型解释性方法，我们在ImageNet-Segmentation [16]数据集上进行弱监督图像分割实验。除了可记忆性映射和原注意力映射，我们还与LIME [42]、梯度传播方法GradCAM [44]和Layer-wise Relevance Propagation方法LRP [4]进行比较。目标是预测一个精确的掩模在感兴趣对象之间没有像素级的监督，其中有一个二元掩模作为ground-truth标签。我们从表1中记录了分割结果，从其中观察到我们的方法IA-RED²在所有其他方法中显著表现出色。作为一个专门的方法来解释CNN的可解释性，我们发现GradCAM在这个任务上表现不佳。我们猜测这是由于CNN和视觉变换器之间的显著差异。

4.2 Redundancy Reduction on Recognition Tasks

在这个部分，我们对图像识别任务和视频动作识别任务进行实验。我们证明了我们的方法可以逐级减少输入patch token的冗余性，同时具有定性和定量结果。
Figure 4: We visualize the hierarchical redundancy reduction process of our method with the DeiT-S model. The number on the upper-left corner of each image indicates the ratio of the remaining patches. From left to right, we can see that the network drops the redundant patches and focuses more on the high-level features of the objects. Best viewed in color.

patch, (3) attention baseline, which drops the patch tokens based on the raw attention map in Block_1. For the baseline methods, we adjust the threshold to set the drop-out rate as 30%, thus there would 30% of the patch tokens be discarded right after the positional embedding layer. Note that all of the baseline methods need re-training. For the attention baseline, since the patches are dropped according to different strategies, we fine-tune the backbone network to make it adapt to the fewer-patch case. Thus our method will not increase training time compared to the baseline methods. We choose the model of our method with the similar inference speed of (1), which would be the baseline with the fastest speed as it does not need any pre-process to the patch tokens, to fairly compare the performance. We test the inference speed in terms of frames per second (fps) of each method on a single NVIDIA Tesla V100-32GB GPU with PyTorch 1.7 and CUDA 10.2. We list our quantitative results in Table 2. In Figure 4, we visualize several examples of hierarchically dropping the patch tokens at different groups, where we can see that our model takes almost all of the tokens at the lower level of the network (the first group), then drops the patches on the background and focuses on the entire object of interest at the middle level (the second group). And finally, it focuses on the part-level stuff of the object at the higher level (the third group).

To further verify the effectiveness of our approach, we compare with a teacher-student baseline, by following the distillation process in DeiT [53]. We use DeiT-S as the teacher model and customize a student model by reducing the depth of the DeiT-S so that the student model contains only around 70% FLOPs of the DeiT-S (similar to the FLOPs of our method applied to DeiT-S). We notice that the student model achieves a top-1 accuracy of 76.0%, while our method got 79.1% top-1 accuracy on ImageNet1K with additional benefits from good model interpretability that shows what is the informative region for the correct prediction of classification.

Results of Video Action Recognition. We further explore the redundancy reduction strategies on the video action recognition task. Similar to the image task, we compare our method with (1) random baseline and (2) attention map baseline. Besides these two, we devise the (3) temporal difference baseline, which calculates the $L_2$ distance between the patch tokens at $T$ and $(T - 1)$ time step. For those tokens that have a longer distance to the previous one, we assume they have larger entropy thus need to be kept. For the patch tokens sampled from the initial frame, we set their previous tokens as zero. We list the results in Table 3. We can see that our method outperforms the attention baseline while worse than the random and temporal difference baseline. Although our method does not get the best results of the four redundancy reduction methods, it learns to identify the informative patches among thousands of input patch tokens, which will be further illustrated in the supplementary material. We guess the reason why the random baseline performs better is that the input redundancy of video is significantly higher than that in the image, which makes the model quite robust to random patch dropping as the similar technique is applied in the training process.
window size of Sinkhorn Transformer and Routing Transformer to 197. We notice that the Sinkhorn Transformer model archives 77.9% top-1 accuracy with 720 fps inference speed, while Routing Transformer achieves 77.5% top-1 accuracy with 8.7 GFLOPs. Moreover, our model can be easily improved by using a stronger backbone to provide a better accuracy-speed trade-off. Since our method does not alter the weights of the original model, it is very convenient to use as a model interpretability method for vision transformers.

We conduct additional baseline experiments by applying the Sparse Sinkhorn Attention \cite{52} and Routing Transformer \cite{43} to the DeiT-S model. Since the input sequential length to the DeiT-S model is fixed to 197, we set the local window size of Sinkhorn Transformer and Routing Transformer to 197. We notice that the Sinkhorn Transformer model archives 77.9% top-1 accuracy with 720 fps inference speed, while Routing Transformer achieves 77.7% top-1 accuracy on ImageNet1k and 663 fps on an NVIDIA Tesla V100 GPU. In contrast, our method obtains 79.1% top-1 accuracy with the inference speed of 1360 fps. Furthermore, we compare with Linformer \cite{55} and observe that it only gets the top-1 accuracy of 75.7% on ImageNet1k. These results show the efficacy of IA-RED\(^2\) over existing data-dependent sparse transformers in reducing the redundancy of vision transformers.

**Applicability of IA-RED\(^2\).** Our approach is model-agnostic, which allows it to serve as a plugin operation for a wide range of sequence-based vision transformer architectures. Our method can be adopted to prune tokens in data-independent transformers like Swin \cite{34}, which adopt complex modifications by introducing CNN-like local windows. But since the number of tokens in different local windows will be different after sparsification, it can be hard to achieve additional speedup on top of such models. However, our model can be easily improved by using a stronger backbone to provide a better accuracy-speed trade-off compared to the Swin transformer. For example, with CaiT-S24-224 \cite{54} as the backbone, we obtain 82.9% top-1 accuracy with only 7.5 GFLOPs (the original CaiT model got 83.5% top-1 accuracy with 9.4 GFLOPs), which is much better than the DeiT-B \cite{53} (81.8% top-1 accuracy and 16.8 GFLOPs) and comparable to the Swin-S (83.3% top-1 accuracy with 8.9 GFLOPs) and Swin-B (83.5% top-1 accuracy with 15.4 GFLOPs). Moreover, our method for interpretability does not require fine-tuning of the original model. Results in Table 2 and 3 do not include the fine-tuning step, which is not essential in our method and is only used for getting better accuracy-speed trade-offs. Since our method does not alter the weights of the original model, it is very convenient to use as a model interpretability method for vision transformers.

**Is Data-level Redundancy Orthogonal to the Model-level?** Contrary to those works \cite{19,23,85} prune the model-level redundancy, our approach seeks to reduce the data-level redundancy. To further study these two counterparts, we start by choosing the magnitude-based weight pruning approach \cite{85} as the subject. The pruning method is applied to all of the FC layers in the transformer. We first plot the trade-off curves between accuracy and efficiency of the weight pruning and our IA-RED\(^2\) in Figure 5, where we can see that our IA-RED\(^2\) outperforms the weight pruning especially when the FLOPs reduction ratio is high. Then we combine these two methods to see if they are complementary to each other: for each compression step, we choose the model with higher accuracy achieved by either increasing the weight pruning ratio or lifting the threshold of our multi-head interpreter to

| Method   | speed | clip-1  | video-1 |
|----------|-------|---------|---------|
| original | ≤24.0 | 28.2    | 23.8    |
| random   | ≥81.0 | 34.3    | 28.2    |
| attention| ≥81.0 | 38.1    | 31.4    |
| temp. diff. | ≥81.0 | 32.3 | 26.9 |
| ours     | ≥81.0 | 35.3    | 29.1    |

**Comparison with Data-dependent Sparse Transformers.** We conduct additional baseline experiments by applying the Sparse Sinkhorn Attention \cite{52} and Routing Transformer \cite{43} to the DeiT-S model. Since the input sequential length to the DeiT-S model is fixed to 197, we set the local window size of Sinkhorn Transformer and Routing Transformer to 197. We notice that the Sinkhorn Transformer model archives 77.9% top-1 accuracy with 720 fps inference speed, while Routing Transformer achieves 77.7% top-1 accuracy on ImageNet1k and 663 fps on an NVIDIA Tesla V100 GPU. In contrast, our method obtains 79.1% top-1 accuracy with the inference speed of 1360 fps. Furthermore, we compare with Linformer \cite{55} and observe that it only gets the top-1 accuracy of 75.7% on ImageNet1k. These results show the efficacy of IA-RED\(^2\) over existing data-dependent sparse transformers in reducing the redundancy of vision transformers.

**Figure 5:** We plot the redundancy reduction results of weight pruning, our IA-RED\(^2\), and the combination of them, where the X axis represents the FLOPs reduction ratio of all linear layers in the DeiT-S, and Y axis represents the top-1 accuracy on ImageNet. For a fair comparison, we do not finetune the network after we reduce the redundancy. With the combination of our IA-RED\(^2\) and the weight pruning method, the model can be directly accelerated by 1.7× without finetuning while suffering only a 1.7% accuracy drop.
Table 4: Redundancy reduction results of our IA-RED\(^2\) with the DeiT-Base in different resolutions. To fairly compare the ratio of the redundancy patches, we keep the parameters of MSA-FFN modules the same as the original and only optimize the multi-head interpreters.

| resolution | method   | speed (fps) | FLOPs \(_{avg}\) | Top-1 | speedup ratio | gap |
|------------|----------|-------------|-----------------|-------|---------------|-----|
| 224×224    | original | 316.8       | 16.8 G          | 81.8  | 1.42×         | 1.5%|
| ours       | 452.5    | 11.8 G      | 80.3            |       |               |     |
| 384×384    | original | 87.0        | 49.4 G          | 82.8  | 1.48×         | 0.9%|
| ours       | 129.6    | 34.7 G      | 81.9            |       |               |     |

Table 5: Results of weakly-supervised image segmentation and image classification using different blocks. We use our method based on the training with DeiT-S model.

| Blocks   | Weakly-Supervised Segmentation | Image Classification |
|----------|-------------------------------|----------------------|
|          | pixel accuracy | mAcc | mIoU | FLOPs | Top-1 | Top-5 |
| Block_0  | 68.3            | 50.5 | 37.1 | 2.9 G | 78.6  | 94.2  |
| Block_1  | 67.9            | 61.8 | 46.4 | 3.3 G | 78.4  | 94.1  |
| Block_2  | 71.9            | 55.7 | 42.6 | 3.6 G | 79.3  | 94.6  |

reduce more redundant tokens. We observe that the combined approach achieves the best trade-off, suggesting that the proposed data-level redundancy is orthogonal to the model-level redundancy, and our method is complementary to the weight pruning method.

**Does the Higher Resolution have More Redundancy?** From Figure 4, we can see the redundancy varies depending on the input instance: images with more background or small features which can identify the object tend to have more redundancy while the images with more complicated object always need more computation. Intuitively, as the redundancy is input-data-dependent, the input data with higher resolution would contain more redundancy. To validate this, we conduct the ablation study in Table 4 where we keep the reduction ratio of the computational cost the same and compare the accuracy loss of the models in different resolutions. We find that the model which takes higher resolution suffers a lower performance decrease than that with the lower resolution, which supports that input data in higher resolution tends to contain more redundancy.

**Effect of the Number of Groups D.** We conduct an ablation study on the number of groups \(D = 2\), \(D = 3\), and \(D = 4\) on ImageNet-1K dataset. Under the same level of computational budget (\(~2.9\) GFLOPs), we find that the 3-group framework used in our approach (79.1% top-1 accuracy) performs slightly better than the 2-group (78.6% top-1 accuracy) and the 4-group (78.8% top-1 accuracy) framework. All of them have good trade-offs between accuracy and speed.

**Effect of Different Blocks in Raw Attention Baseline.** We provide both the segmentation results and classification results of Block_0, Block_1, and Block_2 in Table 5. From the segmentation results, we can see that the attention map of Block_1 outperforms Block_0 and Block_2 by a large margin in terms of mean accuracy and mean IoU. That’s why we chose Block_1 as our baseline. From the classification results, we can see that Block_1 and Block_0 have similar performance on the classification task on ImageNet-1k. However, Block_1 suffers a slightly higher computational cost. Block_2 performs the best, but to get the attention map of Block_2, we need to forward two full blocks of the original vision transformer, which introduces additional computational cost. Additional results and analysis including more visualizations are included in the supplementary material.

5 Conclusions
In this work, we propose a novel interpretability-aware redundancy reduction framework for the recent vision transformer, named IA-RED\(^2\). We show that IA-RED\(^2\) hierarchically reduces the computational cost and speeds up the vision transformer effectively with human-understandable trajectories. Experiments are conducted on image classification and video understanding tasks, where the proposed IA-RED\(^2\) is demonstrated to be both model-agnostic and task-agnostic. We finally compare our IA-RED\(^2\) with the model compression approaches, such as weight pruning, to demonstrate the complementarity between them.
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A Pseudo Code of Our Training Process

To make our training process clearer, we present the details of our training process by pseudo code in Alg. 1. We take the training of DeiT-S for example, where the \( D = 3 \). For each groups, we spend 10 epochs to train the multi-head interpreter and then 20 epochs to train the rest MSA-FFN blocks.

\[
\text{Algorithm 1: Optimize multi-head interpreters and MSA-FFN blocks on DeiT-S.}
\]

\[
\text{Require: A token sequence } X \text{ right after the positional embedding and its label } Y.
\]

\[
\text{for } i \leftarrow 1 \text{ to } D \text{ do}
\]

\[
\text{for } j \leftarrow 1 \text{ to } 10 \text{ do}
\]

\[
\text{for each iteration do}
\]

\[
R \leftarrow \text{Reward}(X, Y \mid W^1_p, W_b)
\]

\[
\text{Compute_Policy_Gradient}(R)
\]

\[
W^1_p \leftarrow \text{Update_Parameters}(W^1_p)
\]

\[
\text{end for}
\]

\[
\text{end for}
\]

\[
\text{for } j \leftarrow 11 \text{ to } 30 \text{ do}
\]

\[
\text{for each iteration do}
\]

\[
L \leftarrow \text{CrossEntropyLoss}(X, Y \mid W^1_i, W_b)
\]

\[
\text{Compute_Gradient}(L)
\]

\[
W^D_b \leftarrow \text{Updated_Parameters}(W^D_b)
\]

\[
\text{end for}
\]

\[
\text{end for}
\]

\[
\text{end for}
\]

where \( D \) is the number of the groups we defined in Section 3 of the main paper, \( W_p \) denotes the parameters of the multi-head interpreters, \( W_b \) denotes the parameters of the MSA-FFN blocks.

B Discussion on the Training Time of Our Method

The 90-epoch training for DeiT-S model takes around 4.5 hours using 24 NVIDIA Tesla V100-32GB GPUs. For one third of all the epochs, we train the multi-head interpreters using REINFORCE, which does not require gradients for the backbone network and saves a lot of computation.

C Random Baseline with Different Seeds

To understand how different seeds affect the experiment results, we provide the results of random dropping and dropping with our learned policy with DeiT-S using four random seeds in the table below. We can see that our method consistently outperforms the random baseline with different seeds.

| method     | Top-1 (s1) | Top-1 (s2) | Top-1 (s3) | Top-1 (s4) | Average Top-1 |
|------------|------------|------------|------------|------------|---------------|
| random     | 78.4%      | 78.3%      | 78.5%      | 78.3%      | 78.4%         |
| Ours       | 79.1%      | 78.8%      | 79.0%      | 79.2%      | 79.0%         |

D REINFORCE vs. Straight-through Gumbel

We also explore training with straight-through Gumbel instead of REINFORCE to be part of our approach. However, we find that Gumbel does not consistently highlight the informative region. In most cases, it highlights the background region instead of foreground objects. Here we provide the comparison of the REINFORCE method and straight-through Gumbel method on the DeiT-S model. Under the same level of FLOPs of 3.0G (Gumbel) versus 2.9G (REINFORCE), the Top-1 accuracy on ImageNet-1K dataset are 78.8% and 79.1% respectively. The results of the Gumbel method are
obtained by discarding the patch tokens which have relatively higher softmax value due to the fact that, in Gumbel method, the background region tends to have higher softmax value.

E Effect of Threshold in Discarding Tokens

We vary the threshold of $I_{i,j}$ to 0.48, 0.49, 0.50, 0.51, and 0.52, to see how the performance of the DeiT-B model would change. The results are shown in Table 7, where we find that with a higher threshold, we get a more efficient model. While lowering the threshold, we get a more accurate model. Thus the threshold of $I_{i,j}$ can be regarded as a trade-off factor between accuracy and efficiency.

Table 7: The performance of the DeiT-B model with different thresholds in discarding tokens.

| Threshold | 0.48 | 0.49 | 0.50 | 0.51 | 0.52 |
|-----------|------|------|------|------|------|
| FLOPs     | 16.5 G | 15.3 G | 11.8 G | 8.2 G | 4.9 G |
| Top-1     | 81.7% | 81.5% | 80.9% | 77.5% | 63.7% |

F Ablation Study on Square Reward and Insights on $\tau$

We jointly study the effect of replacing the squared reward with linear and changing the value of $\tau$ in Eq. 2 in the table below. We can see from that table that, by changing $\tau$ we can get different trade-offs between accuracy and efficiency. Also, without squared reward, we can see that the accuracy-efficiency trade-offs will be more sensitive to the changing of the $\tau$.

Table 8: The effect of square reward and different $\tau$.

| $\tau$ | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
|--------|-----|-----|-----|-----|-----|-----|
| square reward | Yes | Yes | Yes | No | No | No |
| Top-1 | 76.0% | 78.1% | 79.1% | 79.1% | 70.9% | 78.2% |
| FLOPs | 2.5 G | 2.9 G | 3.4 G | 0.4 G | 2.2 G | 3.1 G |

G More Interpretability Results and Demo Tool

In this section, we present more visualization results on both image and video tasks. We plot more interpretability results of our method in Figure 6. Then, we show more examples of hierarchical redundancy reduction process in Figure 7. Finally, in Figure 8, we visualize the input redundancy reduction results of our method on the video action recognition task, where we experiments with the JointST TimeSformer [3] on the Kinetics-400 dataset [7].

We further provide an interpretation tool for the reader who want to play the interpretability of our model. The usage of the tool is quite simple: python interpreter.py -p {image_path} -o {output_dir}. An environment with Python==3.6 (or above), torch==1.7 (or above) and timm==0.3.2 (or above) installed is required to run the tool.

H Broader Impact

Our work eases the suffering of heavy computational cost for the vision transformer, which could save more energy and reduce the carbon emissions for the industry. The interpretability which emerges in our method help we human to understand what happening inside the vision transformer. However, the potential negative impact would be that, since our method makes neural networks easier to run and more understandable to everyone, it may cause the abuse of AI technology.
Figure 6: We visualize more examples with heatmaps which highlight the informative region of the input images of MemNet, raw attention at the second block, and our method with DeiT-S model.
Figure 7: More examples of our hierarchical redundancy reduction process of our method with DeiT-S model. The number on the upper-left corner of each image indicates the ratio of the remaining patches. Best viewed in color.
Figure 8: We visualize the redundancy results of our method with the TimeSformer model. The number on the upper-left corner of each image indicates the ratio of the remaining patches. We can see that our method manages to filter the redundant patches and keeps the informative patches which are important for the final prediction.