ATS: Adaptive Token Sampling For Efficient Vision Transformers

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Abstract

While state-of-the-art vision transformer models achieve promising results for image classification, they are computationally very expensive and require many GFLOPs. Although the GFLOPs of a vision transformer can be decreased by reducing the number of tokens in the network, there is no setting that is optimal for all input images. In this work, we therefore introduce a differentiable parameter-free Adaptive Token Sampling (ATS) module, which can be plugged into any existing vision transformer architecture. ATS empowers vision transformers by scoring and adaptively sampling significant tokens. As a result, the number of tokens is not anymore static but it varies for each input image. By integrating ATS as an additional layer within current transformer blocks, we can convert them into much more efficient vision transformers with an adaptive number of tokens. Since ATS is a parameter-free module, it can be added to off-the-shelf pretrained vision transformers as a plug and play module, thus reducing their GFLOPs without any additional training. However, due to its differentiable design, one can also train a vision transformer equipped with ATS. We evaluate our module on the ImageNet dataset by adding it to multiple state-of-the-art vision transformers. Our evaluations show that the proposed module improves the state-of-the-art by reducing the computational cost (GFLOPs) by 37\% while preserving the accuracy.

1. Introduction

Over the last ten years, there has been tremendous progress for image classification in light of new and complex deep learning architectures, which are based on variants of Convolutional Neural Networks (CNNs) \cite{alexnet, vgg, resnet}. Recently, vision transformers have shown promising results for image classification \cite{vit, deit, swin, mvit} compared to convolution neural networks. While vision transformers have a superior representation power, high computational cost of transformer blocks make them unsuitable for many edge devices.

The computational cost of a vision transformer grows quadratically with respect to the number of tokens it uses. In order to prune the number of tokens and thus the computational cost of a vision transformer, DynamicViT \cite{dynamicvit} proposes to train a token scoring neural network to predict which tokens are redundant. The approach then keeps a fixed ratio of tokens at each stage. Although DynamicViT reduces the GFLOPs of a given network, the scoring network introduces an additional computational overhead. Furthermore, the scoring network needs to be trained together with the vision transformer and it requires to modify the loss function by adding additional loss terms and hyperparameters. A further limitation of DynamicViT is that it needs to be re-trained if the fixed target ratios need to be changed, \textit{e.g.}, due to deployment on a different device. This strongly limits the application scenarios.

In this work, we propose an approach that reduces the
Figure 2: The Adaptive Token Sampler (ATS) can be integrated into the self-attention layer of any transformer block of a vision transformer model (left). The ATS module takes at each stage a set of input tokens $I$. The first token is considered as the classification token in each block of the vision transformer. The attention matrix $A$ is then calculated by the dot product of the queries $Q$ and keys $K$, scaled by $\sqrt{d}$. We use the attention weights $A_{1,1}, \ldots, A_{1,N+1}$ of the classification token as significance scores $S \in \mathbb{R}^N$ for pruning the attention matrix $A$. To reflect the effect of values $V$ on the output tokens $O$, we multiply the $A_{1,j}$ by the magnitude of the corresponding value $V_j$. We select the significant tokens using inverse transform sampling over the cumulative distribution function of the scores $S$. Having selected the significant tokens, we then sample the corresponding attention weights (rows of the attention matrix $A$) to get $A'$. Finally, we softly downsample the input tokens $I$ to output tokens $O$ using the dot product of $A'$ and $V$.

number of tokens of any given vision transformer, but that does not have the limitations of DynamicViT and that is more efficient. The approach is motivated by the observation that not all image information is needed to classify an image since parts of an image are redundant or irrelevant for the classification task. The amount of relevant information, however, depends on the image itself. For instance, Fig.7 shows examples where only a few or many patches are required to classify the image correctly. The same holds for the number of tokens that are used at each stage as illustrated in Fig.3. We therefore propose an approach that automatically selects the right number of tokens at each stage and for each image, i.e., the number of selected tokens varies at all stages and for all images as shown in Fig.6. This in contrast to [27] where the ratio of selected tokens needs to be specified for each stage and it is constant after training. This means that in order to achieve a certain reduction of GFLOPs, the static number of tokens will on one hand discard important information for challenging images, which results in a decrease of the classification accuracy. On the other hand, it will use more tokens than necessary for the easy cases and thus waste computational resources. In this work, we therefore address the question of how a transformer can dynamically adapt its computational resources in a way such that not more resources than necessary are used for each input image.

To this end, we introduce a novel Adaptive Token Sampler (ATS) module. ATS is a differentiable parameter-free module that can sample significant tokens over the input tokens in an adaptive manner. To do so, we first assign scores to the input tokens by employing the attention weights of the classification token in the self-attention layer, and then select a subset of the tokens using inverse transform sampling over the scores. Finally, we softly downsample the output tokens such that the redundant information is removed from the output tokens with the least amount of information loss. In contrast to [27], the approach does not add any additional parameters that need to be learned to the network. The ATS module can thus be added to any off-the-shelf pre-trained vision transformer without any further training or the network with the differentiable ATS module can be further fine-tuned.
We demonstrate the efficiency of the proposed adaptive token sampler by integrating it into the current state-of-the-art vision transformers such as DeiT [32] and CvT [36]. As shown in Fig. 1, the approach reduces significantly the GFLOPs of vision transformers of various sizes without significant loss of accuracy. We evaluate the effectiveness of our method by comparing it with other methods for reducing the number of tokens, including DynamicViT [27] and Hierarchical Pooling [24]. Extensive experiments on the ImageNet dataset show that our method outperforms existing methods and provides the best trade-off between computational cost and classification accuracy. In summary, our contributions are:

- We propose a simple yet effective module, which automatically adapts the number of tokens in a transformer block based on the redundancy of the input data.
- We propose a novel token selection strategy which benefits from the inherent self-attention mechanism in vision transformers to score the tokens without adding an additional computational overhead or parameters.
- We propose a novel soft downsampling strategy which extends the traditional self-attention mechanism capabilities by providing soft downsampling capabilities to them.
- Our experiments on the ImageNet dataset show the efficiency of our method compared to other state-of-the-art methods.

In a nutshell, the adaptive token sampler is capable of significantly scaling down the computational cost of off-the-shelf vision transformers and it is therefore very useful for real-world vision-based applications.

2. Related Work

The transformer architecture, which was initially introduced in the NLP community [33], has demonstrated promising performance on various computer vision tasks [7, 32, 22, 43, 28, 1, 42, 3, 39, 41]. ViT [7] has followed the standard transformer architecture to tailor a network that is applicable to images. ViT splits an input image into a set of non-overlapping patches and produces patch embeddings of lower dimensionality. The network then adds positional embeddings to the patch embeddings and passes them through a number of transformer blocks. An extra learnable class embedding is also added to the patch embeddings to perform classification. Although ViT has shown promising results on image classification, it requires an extensive amount of data to generalize well. DeiT [32] addressed this issue by introducing a distillation token designed to learn from a teacher network. Additionally, it surpassed the performance of ViT. LV-ViT [18] proposed a new objective function for training vision transformers and achieved better performance.

Besides accuracy of neural networks, their efficiency plays an important role in deploying them on edge devices. A wide range of techniques have been proposed to speed up the inference of these models. To obtain deep networks that can be deployed on different edge devices, some works [30] proposed more efficient architectures by carefully scaling the depth, width, and resolution of a baseline network based on different resource constraints. Some others [15] have tried to meet such resource requirements by introducing hyper-parameters, which can be tuned to build efficient light-weight models. Some works [8, 34] have adopted quantization techniques to compress and accelerate deep models. Besides quantization techniques, other approaches such as channel pruning [13], run-time neural pruning [26], low-rank matrix decomposition [38, 16] and knowledge distillation [14, 21] have been used to speed up deep networks.

In addition to the works that aim to accelerate inference of convolutional neural networks, many other works attempted to improve the efficiency of transformer-based models. In the NLP area, Star-Transformer [10] reduced the number of connections from $n^2$ to $2n$ by changing the fully-connected topology into a star-shaped structure. Tiny-BERT [19] improved the network’s efficiency by distilling the knowledge of a large teacher BERT into a tiny student network. PoWER-BERT [9] reduced the inference time of the BERT model by identifying and removing redundant and less-informative tokens based on their importance scores estimated from the self-attention weights of the transformer blocks. In the computer vision area, DynamicViT [27] proposed an additional prediction module that predicts the importance of tokens and discards uninformative tokens for the image recognition task. Hierarchical Visual Transformer (HVT) [24] employs token pooling, which is similar to the feature maps down-sampling in convolutional neural networks, to remove redundant tokens.

3. Adaptive Token Sampler

Current state-of-the-art vision transformers are computationally expensive since the computational cost grows quadratically with respect to the number of tokens. The number of tokens is also static at all stages of the network and corresponds to the number of input patches where the accuracy increases as the number of patches increases. Convolutional neural networks deal with the computational cost by reducing the resolution within the network using various pooling operations. This means that the spatial resolution decreases at later stages of the network. However, it is not straightforward to apply such simple strategy to vision transformers since the tokens are permutation invariant. Moreover, such static downsampling, i.e. pooling operations with fixed kernels, is not optimal since a fixed down-
sampling rate can on one hand discard important information at some locations of the image like details of the object and on the other hand still include many redundant features that do not contribute to the classification accuracy as it is for instance the case for an image with a homogeneous background. We therefore propose an approach that dynamically adapts the number of the tokens at each stage of the network to the input image such that important information is not discarded and no computational resources are wasted for processing redundant information.

To this end, we propose our novel Adaptive Token Sampler (ATS) module. ATS is a parameter-free differentiable module to sample significant tokens over the input tokens. In our ATS module, we first assign scores to the \( N \) input tokens, and then select a subset of the tokens based on the score. The upper bound of the GFLOPs can be set by dynamically adapting the number of the tokens at each stage of the network. We first assign scores to the tokens, and then select a subset of the tokens based on their scores. However, such an approach does not perform well as we will show in the experiments and it does not adaptively select \( K' \leq K \) tokens. The reason why taking the top-\( K \) does not work well is that it discards all tokens with lower scores. Some of these tokens, however, can be useful in particular at earlier stages when the features are less discriminative. For instance, multiple tokens with similar keys, as they occur in early stages, will lower their attention weights due to the Softmax. Although one of these tokens would be useful for later stages, taking the top-\( K \) tokens might discard all of them. We thus propose to sample them based on the scores. In this case, the probability that one of several similar tokens is sampled is equal to the sum of the scores of the similar tokens. We also observe that the proposed sampling procedure selects more tokens than the proposed approach.

### 3.1. Token Scoring

Let \( \mathcal{I} \in \mathbb{R}^{(N+1)\times d} \) be the input tokens of a self-attention layer with \( N + 1 \) tokens. Before forwarding image tokens through the model, ViT concatenates a classification token to the image tokens. The corresponding output token at the final transformer block is then fed to the classification head to get the class probabilities. Practically speaking, this token is placed as the first token in each block. Thus the first token is considered as a classification token. While we keep the classification token, our goal is to reduce the output tokens \( \mathcal{O} \in \mathbb{R}^{(K' + 1)\times d} \) such that \( K' \) is dynamically adapted based on the input image and \( K' \leq K \leq N \), where \( K \) is a parameter that controls the maximum number of sampled tokens. Fig.6 shows how the number of sampled tokens \( K' \) varies for different input images and different stages of a network. We first describe how each token is scored.

In a standard self-attention layer [33], the queries \( \mathcal{Q} \in \mathbb{R}^{(N+1)\times d} \), keys \( \mathcal{K} \in \mathbb{R}^{(N+1)\times d} \), and values \( \mathcal{V} \in \mathbb{R}^{(N+1)\times d} \) are computed from the input tokens \( \mathcal{I} \in \mathbb{R}^{(N+1)\times d} \). The attention matrix \( \mathcal{A} \) is then calculated by the dot product of the queries and keys, scaled by \( \sqrt{d} \):

\[
\mathcal{A} = \text{Softmax} \left( \mathcal{Q} \mathcal{K}^T / \sqrt{d} \right). \tag{1}
\]

Due to the Softmax, each row of \( \mathcal{A} \in \mathbb{R}^{(N+1)\times(N+1)} \) sums up to 1. The output tokens are then a combination of the values vectors weighted by the attention weights:

\[
\mathcal{O} = \mathcal{A} \mathcal{V}. \tag{2}
\]

Each row of \( \mathcal{A} \) contains the attention weights of an input token. The weights indicate the contribution of the values of all tokens for the output token. Since \( \mathcal{A}_{1,j} \) contains the attention weights for the classification token, it represents the importance of the input token \( j \) for the output classification token. We thus use the weights \( \mathcal{A}_{1,1}, \ldots, \mathcal{A}_{1,N+1} \) as significance scores for pruning the attention matrix \( \mathcal{A} \) as illustrated in Fig.2. Note that \( \mathcal{A}_{1,1} \) is not used since we keep the classification token. Since the output tokens \( \mathcal{O} \) depend on \( \mathcal{A} \) and \( \mathcal{V} \) (2), we also take into account the norm of \( \mathcal{V}_j \). The motivation is that values with a norm close to zero have a low impact and are thus less significant. In the experiments, we show that multiplying \( \mathcal{A}_{1,j} \) with the norm of \( \mathcal{V}_j \) improves the results. The significance score of the token \( j \) is thus given by

\[
S_j = \frac{\mathcal{A}_{1,j} \times ||\mathcal{V}_j||}{\sum_{i=2}^{K} \mathcal{A}_{1,i} \times ||\mathcal{V}_i||}. \tag{3}
\]

For a multi-head attention layer, we calculate the scores for each head and sum it over all heads.

### 3.2. Token Sampling

Having computed the score for each token, we can prune the corresponding tokens from the attention matrix \( \mathcal{A} \). To do so, a naive approach would be to select the top-\( K \) tokens based on their scores. However, such an approach does not perform well as we will show in the experiments and it does not adaptively select \( K' \leq K \) tokens. The reason why taking the top-\( K \) does not work well is that it discards all tokens with lower scores. Some of these tokens, however, can be useful in particular at earlier stages when the features are less discriminative. For instance, multiple tokens with similar keys, as they occur in early stages, will lower their attention weights due to the Softmax. Although one of these tokens would be useful for later stages, taking the top-\( K \) tokens might discard all of them. We thus propose to sample them based on the scores. In this case, the probability that one of several similar tokens is sampled is equal to the sum of the scores of the similar tokens. We also observe that the proposed sampling procedure selects more tokens at earlier stages than at later stages as shown in Fig.3.

For the sampling, we propose to use the inverse transform sampling to sample the tokens based on their corresponding scores \( S \) (3). Since the scores are normalized, they can be interpreted as probabilities and we can calculate the cumulative distribution function (CDF) of \( S \):

\[
\text{CDF}_j = \sum_{j=2}^{j=i} S_j. \tag{4}
\]

Note that we start with the second token since we keep the first token. Having the cumulative distribution function, we obtain the sampling function by taking the inverse of the CDF:

\[
\Psi(k) = \text{CDF}^{-1}(k). \tag{5}
\]
In this section, we evaluate our ATS module by adding it to different backbone models and evaluating them on ImageNet [5], a large-scale image classification dataset. In addition, we perform several ablation studies to better analyze our method. We evaluate our proposed method on the ImageNet [5] dataset with 1.3M images and 1K classes. We use the standard training/testing splits and protocols provided by the ImageNet dataset. If not otherwise stated, in all of our experiments, the number of output tokens of an ATS module (K) are bounded from above by the number of its input tokens. For example, we set K = 197 in DeiT-S [32]. The fine-tuned models are initialized by their backbones’ pre-trained weights and trained for 30 epochs using PyTorch AdamW optimizer (lr= 5e−4, batch size = 8 × 96). We use the cosine scheduler for training the networks. For more implementation details, please refer to the supplementary material.

### 4.1. Ablation Experiments

First, we analyze different setups for our ATS module. Then, we investigate the efficiency and effects of our ATS module when incorporated in different models. If not otherwise stated, we use the pre-trained DeiT-S [32] model as the backbone and we do not fine-tune the model after adding the ATS module. We integrate the ATS module into the stage 3 of the DeiT-S [32] model. We report the results on the ImageNet-1K validation set in all of our ablation studies.

#### Significance Scores

As mentioned in Sec.3.1, we use the attention weights of the classification token as significance scores for selecting our candidate tokens. In this experiment, we evaluate different approaches for calculating significance scores. To this end, instead of directly using the attention weights of the classification token we sum over the attention weights of all tokens (rows of the attention matrix) to find tokens with highest significance over other tokens. We show the results of this method in Fig.4 labeled as Self-Attention score. As it can be seen, using the attention weights of the classification token performs better specially in lower FLOPs regimes. The results show that the attention weights of the classification token are a much stronger signal for selecting the candidate tokens. The reason for this is that the classification token will later be used to predict the class probabilities in the final stage of the model. Thus, its corresponding attention weights show which tokens have more impact on the output classification token. Whereas summing over all attention weights only shows us the tokens with highest attention from all other tokens, which may not necessarily be useful for the classification token. To better investigate this observation, we also randomly select another token rather than the classification token and use its attention weights for the score assignment. As shown, this approach performs much worse than the other one both in high and low FLOPs regime. We also investigate using the L2 norms of the values as mentioned in Eq.3. As it can be seen in Fig.4, it improves the results by about 0.2%.

#### Candidate Tokens Selection

As mentioned in Sec.3.2, we employ the inverse transform sampling approach to softly downsample the input tokens. To better investigate this approach, we also evaluate the model’s performance when picking the top K tokens with highest significance scores S. As it can be seen in Fig.5a, our inverse transform sampling approach outperforms the Top-K selection both in high and

where \( k \in [0, 1] \). In other words, the selection scores are used to calculate the mapping function between the indices of the original tokens and the sampled tokens. To obtain \( K \) samples, we can sample \( K \)-times from the uniform distribution \( U[0, 1] \). While such randomization might be desirable for some applications, deterministic inference is in most cases preferred. We therefore use a fixed sampling scheme for training and inference by choosing \( k = \{1/K, \ldots, K/K\} \). Since \( \Psi(\cdot) \in \mathbb{R} \), we choose the nearest integers as the sampling indices.

If a token is sampled more than once, we keep only one instance. As a consequence, the number of unique indices \( K’ \) is often lower than \( K \) as shown in Fig.6. In fact, \( K’ < K \) if there is at least one token with a score \( S_j \geq 2/K \). In the two extreme cases, either only one dominant token is selected and \( K’ = 1 \) or \( K’ = K \) if the scores are more or less balanced. It is interesting to note that more tokens are selected at the earlier stages, when the features are less discriminative and the attention weights are more balanced, and less at later stages as shown in Fig.3. The number and locations of tokens also varies for different input images as shown in Fig.7. For images with a homogeneous background that covers a large part of the image, only few tokens are sampled. The tokens cover the object in the foreground and are sparsely but uniformly sampled from the background. For cluttered images, many tokens are required. This illustrates the importance of making the sampling of the tokens adaptive.

Having the indices of the selected tokens, we refine the attention matrix \( A \in \mathbb{R}^{(N+1) \times (N+1)} \) by selecting the rows that correspond to the selected \( K’ + 1 \) tokens. We denote the refined attention matrix by \( A^* \in \mathbb{R}^{(K’+1) \times (N+1)} \). To obtain the output tokens \( O \in \mathbb{R}^{(K’+1) \times d} \), we thus replace the attention matrix \( A \) by the refined one \( A^* \) in (2) such that:

\[
O = A^* \Psi.
\]

These output tokens are then taken as input for the next stage. In our experimental evaluation, we demonstrate the efficiency of the proposed adaptive token sampler, which can be added to any vision transformer.

### 4. Experiments

In this section, we evaluate our ATS module by adding it to different backbone models and evaluating them on ImageNet [5], a large-scale image classification dataset. Additionally, we perform several ablation studies to better analyze our method. We evaluate our proposed method on the ImageNet [5] dataset with 1.3M images and 1K classes. We use the standard training/testing splits and protocols provided by the ImageNet dataset. If not otherwise stated, in all of our experiments, the number of output tokens of an ATS module (K) are bounded from above by the number of its input tokens. For example, we set K = 197 in DeiT-S [32]. The fine-tuned models are initialized by their backbones’ pre-trained weights and trained for 30 epochs using PyTorch AdamW optimizer (lr= 5e−4, batch size = 8 × 96). We use the cosine scheduler for training the networks. For more implementation details, please refer to the supplementary material.
Figure 3: Visualization of the gradual token sampling procedure in the multi-stage DeiT-S+ATS model. We represent the token sampling results at 9 stages of our multi-stage DeiT-S+ATS model. As it can be seen, at each stage, those tokens that are considered to be less significant to the classification are masked and the ones that have contributed the most to the model’s prediction are sampled. We also visualize the token sampling results with Top-K selection to have a better comparison to our Inverse Transform Sampling.

Figure 4: Impact of different score assignment methods. To achieve different GFLOPs levels, we bound the value of $K$ from above such that the average GFLOPs of our adaptive models over the ImageNet validation set reaches the desired level. For more details, please refer to the supplementary material.

Low GFLOPs regimes. As discussed earlier, our inverse transform sampling approach based on the CDF function of the scores does not hardly discard all tokens with lower significance scores and hence provides a more diverse set of tokens for the following layers. Since earlier transformer blocks are more prone to predict noisier attention weights for the classification token, such a diversified set of tokens can better contribute to the output classification token of the final transformer block. Moreover, the Top-K selection method will result in a fixed token selection rate at every stage that limits the performance of the backbone model. This is shown by the examples in Fig.3. For a cluttered image (bottom), inverse transform sampling keeps a higher number of tokens across all transformer blocks compared to the Top-K selection and hence preserves the accuracy. On the other hand, for a less detailed image (top), inverse transform sampling will retain less tokens, which results in less computation cost.

Model Scaling. Another common approach for changing the GFLOPs/accuracy trade-off of networks is to change the channel dimension. To demonstrate the efficiency of our adaptive token sampling method, we thus vary the dimensionality. To this end, we first train several DeiT mod-
Figure 5: For the model with Top-K selection (fixed-rate sampling) (5a), we set $K$ such that the model operates at a desired GFLOPs level. In all three plots, we control the GFLOPs level of our adaptive models as in Fig.4. We use DeiT-S[32] for these experiments. For more details, please refer to the supplementary material.

eels with different embedding dimensions. Then, we integrate our ATS module into the stages 3 to 11 of these DeiT backbones and fine-tune the networks. In Fig.1, we can observe that our approach can reduce GFLOPs by 37% while maintaining the DeiT-S backbone’s accuracy. We can also observe that the GFLOPs reduction rate gets higher as we increase the embedding dimensions from 192 (DeiT-Ti) to 384 (DeiT-S). The results show that our ATS module can reduce the computation cost of the models with larger embedding dimensions to their variants with smaller embedding dimensions.

Visualizations To better understand the way our ATS module operates, we visualize our token sampling procedure (Inverse Transform Sampling) in Fig.3. We have incorporated our ATS module in the stages 3 to 11 of the DeiT-S network. The tokens that are discarded at each stage are represented as a mask over the input image. We observe that our DeiT-S+ATS model has gradually removed irrelevant tokens and sampled those tokens which are more significant to the model’s prediction. In both examples, our method identified the tokens that are related to the target objects as the most informative tokens.

Adaptive Sampling In this experiment, we investigate the dynamicity of our adaptive token sampling approach. We evaluate our multi-stage DeiT-S+ATS model on the ImageNet validation set. In Fig.6, we visualize histograms of the number of sampled tokens at each ATS stage. We can observe that the number of selected tokens varies at all stages and for all images. We also qualitatively analyze this nice property of our ATS module in Figs.3 and 7. We can observe that our ATS module selects a higher number of tokens when it deals with detailed and complex images while it selects a lower number of tokens for less detailed images.

Fine-tuning To explore the influence of fine-tuning on the performance of our approach, we fine-tune a DeiT-S+ATS model on the ImageNet training set. We compare the model with and without fine-tuning. As shown in Fig.5b, fine-tuning can improve the accuracy of the model. In this experiment, we fine-tune the model with $K = 197$ but test it with different $K$ values to reach the desired GFLOPs levels.

ATS Stages In this experiment, we explore the effect of single-stage and multi-stage integration of the ATS block into vision transformer models. In the single-stage model, we integrate our ATS module into the stage 3 of DeiT-S. In the multi-stage model, we integrate our ATS module into the stages 3 to 11 of DeiT-S. As it can be seen in Fig.5c, the multi-stage DeiT-S+ATS performs better than the single-stage DeiT-S+ATS. This is due to the fact that a multi-stage DeiT-S+ATS model can gradually decrease the GFLOPs by discarding fewer tokens in earlier stages, while a single-stage DeiT-S+ATS model has to discard more tokens in earlier stages to reach the same GFLOPs level.
Figure 7: Our ATS module adapts the number of tokens for each sample by taking the image content into consideration. ATS samples a lower number of tokens for images with fewer details (top), and higher number of tokens for images with more details (bottom). We show the input image and the token downsampling results after all ATS stages. The masks represent the discarded tokens. For this experiment, we use a multi-stage Deit-S+ATS model.

4.2. Comparison with state-of-the-art

We compare the performances of our adaptive models, which are equipped with the ATS module, with state-of-the-art vision transformers for image classification on ImageNet-1K [5]. Table 1 shows the results of this comparison. We incorporate our ATS module into the stages 3 to 11 of the Deit-S [32] model. We also integrate our ATS module into the 1st to 9th blocks of the 3rd stage of CvT-13 [36] and CvT-21 [36]. We fine-tune the models on the ImageNet-1K train set. For more details, please refer to the supplementary material. As it can be seen, our ATS module decreases the GFLOPs of all vision transformer models without adding any extra parameters to the backbone model. For the Deit-S+ATS model, we observe a 37% GFLOPs reduction with only 0.1% reduction in the top-1 accuracy. For CvT+ATS series, we can also observe a GFLOPs reduction of about 30% with 0.1 – 0.2% reduction in the top-1 accuracy. Comparing the Vision Transformers with ATS to DynamicViT [27] and HVT [24], which add additional parameters to the model, our approach achieves a better trade-off between accuracy and GFLOPs.

5. Conclusion

Designing computationally efficient vision transformer models for image recognition is a challenging task. In this work, we proposed a novel differentiable parameter-free module called Adaptive Token Sampling (ATS) to increase the efficiency of vision transformers for image classification. The new ATS module selects the most informative and distinctive tokens within the stages of a vision transformer model such that as much tokens as needed but not more than necessary are used for each input image. By integrating our ATS module into the attention layers of current vision transformers, which use a static number of tokens, we can convert them into much more efficient vision transformers with an adaptive number of tokens. We showed that our ATS module can be added to off-the-shelf pre-trained vision transformers as a plug and play module, thus reducing their GFLOPs without any additional training. Though, thanks to its differentiable design, one can also train a vision transformer equipped with the ATS module to decrease the accuracy drop. We evaluated our approach on the ImageNet-1K image recognition dataset and incorporated our ATS module into three different state-of-the-art vision transformers. The results demonstrate that the ATS module decreases the computation cost (GFLOPs) between 27% and 37% with a negligible accuracy drop. Although our experiments are focused on vision transformers, we believe that our approach can also work in other domains such as video and audio.

Table 1: Comparison of the multi-stage ATS models with state-of-the-art image classification models with comparable GFLOPs on the ImageNet validation set. We equip DeiT-S [32] and variants of CvT [36] with our ATS module and fine-tune them on the ImageNet train set.
Limitations
Besides all the nice properties of our adaptive token sampling approach, it also has some limitations. In real-time application scenarios, the bottleneck of the system is the highest computation cost of the method. Therefore, the improvements of our adaptive sampling approach will be limited to its upper bound in such scenarios. Although such constraint limits the run-time speed-up of our adaptive sampling method, our approach will still remain more efficient in other aspects, such as energy consumption. Moreover, such constraint could be further resolved by adjusting the upper bound of the ATS module.

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