AdaViT: Adaptive Tokens for Efficient Vision Transformer

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Figure 1. We introduce AdaViT, a method to enable adaptive token computation for vision transformers. We augment the vision transformer block with adaptive halting module that computes a halting probability per token. The module reuses the parameters of existing blocks and it borrows a single neuron from the last dense layer in each block to compute the halting probability, imposing no extra parameters or computations. A token is discarded once reaching the halting condition. Via adaptively halting tokens, we perform dense compute only on the active tokens deemed informative for the task. As a result, successive blocks in vision transformers gradually receive less tokens, leading to faster inference. Learnt token halting vary across images, yet align surprisingly well with image semantics (see examples above and more in Fig. 3). This results in immediate, out-of-the-box inference speedup on off-the-shelf computational platform.

Abstract

We introduce AdaViT, a method that adaptively adjusts the inference cost of vision transformer (ViT) for images of different complexity. AdaViT achieves this by automatically reducing the number of tokens in vision transformers that are processed in the network as inference proceeds. We reformulate Adaptive Computation Time (ACT [17]) for this task, extending halting to discard redundant spatial tokens. The appealing architectural properties of vision transformers enables our adaptive token reduction mechanism to speed up inference without modifying the network architecture or inference hardware. We demonstrate that AdaViT requires no extra parameters or sub-network for halting, as we base the learning of adaptive halting on the original network parameters. We further introduce distributional prior regularization that stabilizes training compared to prior ACT approaches. On the image classification task (ImageNet1K), we show that our proposed AdaViT yields high efficacy in filtering informative spatial features and cutting down on the overall compute. The proposed method improves the throughput of DeiT-Tiny by 62% and DeiT-Small by 38% with only 0.3% accuracy drop, outperforming prior art by a large margin.

1. Introduction

Transformers have emerged as a popular class of neural network architecture that computes network outputs using highly expressive attention mechanisms. Originated from the natural language processing (NLP) community, they have been shown effective in solving a wide range of problems in NLP, such as machine translation, representation learning, and question answering [2, 9, 22, 35, 44]. Recently, vision transformers have gained an increasing popularity in the vision community and they have been successfully applied to a broad range of vision applications, such as image classification [11, 16, 32, 43, 48, 55], object detection [3, 7, 39], image generation [20, 21], and semantic segmentation [28, 52]. The most popular paradigm remains when vision transformers form tokens via splitting an image into a series of ordered patches and perform inter-/intra-calculations between tokens to solve the underlying task. Processing an image with vision transformers remains computationally expensive, pri-
AdaViT, a spatially adaptive inference mechanism that halts inference from dynamically inferred tokens, surpasses prior dynamic approaches in the efficiency tradeoff. Graves [17] proposed adaptive computation time (ACT) to represent the output of the neural module as a mean-field model defined by a halting distribution. Such formulation relaxes the discrete halting problem to a continuous optimization problem that minimizes an upper bound on the total compute. Recently, stochastic methods were also applied to solve this problem, leveraging geometric-modelling of exit distribution to enable early halting of network layers [1]. Figurnov et al. [13] proposed a spatial extension of ACT that halts convolutional operations along the spatial cells rather than the residual layers. This approach does not lead to faster inference as high-performance hardware still relies on dense computations. However, we show that the vision transformer’s uniform shape and tokenization enable an adaptive computation method to yield a direct speedup on off-the-shelf hardware, surpassing prior dynamic approaches in the efficiency-accuracy tradeoff.

In this paper, we propose an input-dependent adaptive inference mechanism for vision transformers. A naive approach is to follow ACT, where the computation is halted for all tokens in a residual layer simultaneously. We observe that this approach reduces the compute by a small margin with an undesirable accuracy loss. To resolve this, we propose AdaViT, a spatially adaptive inference mechanism that halts the compute of different tokens at different depths, reserving compute for only discriminative tokens in a dynamic manner. Unlike point-wise ACT within convolutional feature maps [13], our spatial halting is directly supported by high-performance hardware since the halted tokens can be efficiently removed from the underlying computation. Moreover, entire halting mechanism can be learnt using existing parameters within the model, without introducing any extra parameters. We also propose a novel approach to target different computational budgets by enforcing a distributional prior on the halting probability. We empirically observe that the depth of the compute is highly correlated with the object semantics, indicating that our model can ignore less relevant background information (see quick examples in Fig. 1 and more examples in Fig. 3). Our proposed approach significantly cuts down the inference cost – AdaViT improves the throughput of DeiT-Tiny by 62% and DeiT-Small by 38% with only 0.3% accuracy drop on ImageNet1K.

Our main contributions are as follows:

- We introduce a method for input-dependent inference in vision transformers that allows us to halt the computation for different tokens at different depth.
- We base learning of adaptive token halting on the existent embedding dimensions in the original architecture and do not require extra parameters or compute for halting.
- We introduce distributional prior regularization to guide halting towards a specific distribution and average token depth that stabelizes ACT training.
- We analyze the depth of varying tokens across different images and provide insights into the attention mechanism of vision transformer.
- We empirically show that the proposed method improves throughput by up to 62% on hardware with minor drop in accuracy.

2. Related Work

There are a number of ways to improve the efficiency of transformers including weight sharing across transformer blocks [26], dynamically controlling the attention span of each token [5, 40], allowing the model to output the result in an earlier transformer block [38, 56], and applying pruning [53]. A number of methods have aimed at reducing the computationally complexity of transformers by reducing the quadratic interactions between tokens [6, 23, 24, 41, 47].

We focus on approaches related to adaptive inference that depends on the input image complexity. A more detailed analysis of the literature is present in [19].

**Special architectures.** One way is to change the architecture of the model to support adaptive computations [4, 14, 15, 18, 25, 27, 30, 37, 42, 51, 54]. For example, models that represent a neural network as a fixed-point function can have the property of adaptive computation by default. Such models compute the difference to the internal state and, when applied over multiple iterations, converge towards the solution (desired output). For example, neural ordinary differential equations (ODEs) use a new architecture with repetitive computation to learn the dynamics of the process [10]. Using ODEs requires a specific solver, is often slower than fix depth models and requires adding extra constrains on the model design. [54] learns a set of classifiers with different resolu-
We show complete viability to remove the need for the extra E variant with shared weights and a halting mechanism.

**Stochastic and reinforcement learning (RL) methods.** The depth of a residual neural network can be changed during inference by skipping a subset of residual layers. This is possible since residual networks have the same input and output feature dimensions and they are known to perform feature refinements iteratively. Individual extra models can be learned on the top of a backbone to change the computational graph. A number of approaches [29, 34, 49, 50] proposed to train a separate network via RL to decide when to halt. These approaches require training of a dedicated halting model and their training is challenging due to the high-variance training signal in RL. Conv-AIG [45] learns the conditional gating of residual blocks via the Gumbel-softmax trick. [46] extends the idea to spatial dimension for a token ϵ: $h^l_k = H(t^l_k)$, where $H(\cdot)$ is a halting module. Akin to ACT [17], we enforce the halting score of each token $h^l_k$ to be in the range $0 \leq h^l_k \leq 1$, and use accumulative importance to halt tokens as inference progresses into deeper layers. To this end, we conduct the token stopping when the cumulative halting score exceeds $1 - \epsilon$:

$$N_k = \arg\min_{n \leq L} \sum_{l=1}^{n} h^l_k \geq 1 - \epsilon, \quad (4)$$

where $\epsilon$ is a small positive constant that allows halting after one layer. To further alleviate any dependency on dynamically halted tokens between adjacent layers, we mask out a token $t^l_k$ for all remaining depth $l > N_k$ once it is halted by (i) zeroing out the token value, and (ii) blocking its attention to other tokens, shielding its impact to $t^l_k$ in Eqn. 2. We define $h^L_{1,K} = 1$ to enforce stopping at the final layer for all tokens. Our token masking keeps the computational cost of our training iterations similar to the original vision transformer’s training cost. However, at the inference time, we simply remove the halted tokens from computation to measure the actual speedup gained by our halting mechanism.

We incorporate $H(\cdot)$ into the existing vision transformer block by allocating a single neuron in the MLP layer to do the task. Therefore, we do not introduce any additional learnable parameters or compute for halting mechanism. More specifically, we observe that the embedding dimension $E$ of each token spares sufficient capacity to accommodate learning of adaptive halting, enabling halting score calculation as:

$$H(t^l_k) = \sigma(\gamma \cdot t^l_k + \beta), \quad (5)$$

where $t^l_k$ is a small positive constant that allows halting after one layer. To further alleviate any dependency on dynamically halted tokens between adjacent layers, we mask out a token $t^l_k$ for all remaining depth $l > N_k$ once it is halted by (i) zeroing out the token value, and (ii) blocking its attention to other tokens, shielding its impact to $t^l_k$ in Eqn. 2. We define $h^L_{1,K} = 1$ to enforce stopping at the final layer for all tokens. Our token masking keeps the computational cost of our training iterations similar to the original vision transformer’s training cost. However, at the inference time, we simply remove the halted tokens from computation to measure the actual speedup gained by our halting mechanism.

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embedding before applying the non-linearity. Note that these two scalar parameters are shared across all layers for all tokens. Only one entry of the embedding dimension $E$ is used for halting score calculation. Empirically, we observe that the simple choice of $e = 0$ (the first dimension) performs well, while varying indices does not change the original performance, as we show later. As a result our halting mechanism does not introduce additional parameters or sub-network beyond the two scalar parameters $\beta$ and $\gamma$.

To track progress of halting probabilities across layers, we calculate a remainder for each token as:

$$r_k = 1 - \sum_{i=1}^{N_k-1} h^i_k,$$

that subsequent forms a halting probability as:

$$p^l_k = \begin{cases} 0 & \text{if } l > N_k, \\ r_k & \text{if } l = N_k, \\ h^l_k & \text{if } l < N_k. \end{cases}$$

Given the range of $h$ and $r$, halting probability per token at each layer is always bounded $0 \leq p^l_k \leq 1$. The overall ponder loss to encourage early stopping is formulated via auxiliary variable $r$ (reminder):

$$L_{ponder} := \frac{1}{K} \sum_{k=1}^{K} \rho_k = \frac{1}{K} \sum_{k=1}^{K} (N_k + r_k),$$

where ponder loss $\rho_k$ of each token is averaged. Vision transformers use a special class token $t_{fe}$ to produce the classification prediction, we denote it as $t_c$ for future notations. This token similar to other input tokens is updated in all layers. We apply a mean-field formulation (halting-probability weighted average of previous states) to form the output token $t_o$ and the associated task loss as:

$$L_{task} = C(t_o), \text{ where } t_o = \sum_{l=1}^{L} p^l_c t^l_c. \quad (9)$$

Our vision transformer can then be trained by minimizing:

$$L_{overall} = L_{task} + \alpha_p L_{ponder}, \quad (10)$$

where $\alpha_p$ scales the pondering loss relative to the the main task loss. Algorithm 1 describes the overall computation flow, and Fig. 2 depicts the associated halting mechanism for visual explanation. At this stage, the objective function encourages an accuracy-efficiency trade-off when pondering different tokens at varying depths, enabling adaptive control.

One critical factor in Eqn. 10 is $\alpha_p$ that balances halting strength and network performance for the target application. A larger $\alpha_p$ value imposes a stronger penalty, and hence learns to halt tokens earlier. Despite efficacy towards computation reduction, prior work on adaptive computation [13, 17] have found that training can be sensitive to the choice of $\alpha_p$ and its value may not provide a fine-grain control over accuracy-efficiency trade-off. We empirically observe a similar behavior in vision transformers.

As a remedy, we introduce a distributional prior to regularize $h^l$ such that tokens are expected to exit at a target depth on average, however, we still allow per-image variations. In this case for infinite number of input images we expect the the depth of token to vary within the distributional prior. Similar prior distribution has been recently shown effective
Algorithm 1 Adaptive tokens in vision transformer without imposing extra parameters.

**Input:** tokenized input tensor $\text{input} \in \mathbb{R}^{K \times E}$, $K$, $E$ being token number and embedding dimension; $c$ is class-token index in $K$; $0 < \epsilon < 1$

**Output:** aggregated output tensor $\text{out}$, ponder loss $\rho$

1. $t = \text{input}$
2. $\text{cumul} = 0$  \quad $\triangleright$ Cumulative halting score
3. $\text{R} = 1$  \quad $\triangleright$ Remainder value
4. $\text{out} = 0$  \quad $\triangleright$ Output of the network
5. $\rho = 0$  \quad $\triangleright$ Token ponder loss vector
6. $m = 1$  \quad $\triangleright$ Token mask $m \in \mathbb{R}^{K}$
7. for $l = 1 \ldots L$ do
8.   $t = F^{l}(t \odot m)$
9.   if $l < L$ then
10.      $h = \alpha(\gamma \cdot t_{c,0} + \beta)$  \quad $\triangleright$ $h \in \mathbb{R}^{K}$
11.   else
12.      $h = 1$
13.   end if
14.  $\text{cumul} += h$
15.  $\rho += m$  \quad $\triangleright$ Add one per remaining token
16.  for $k = 1, \ldots, K$ do
17.     if $\text{cumul}_{k} < 1 - \epsilon$ then
18.        $\text{R}_{k} -= h_{k}$
19.     else
20.        $\rho_{k} += \text{R}_{k}$
21.     end if
22.  end for
23.  if $\text{cumul}_{c} < 1 - \epsilon$ then
24.     $\text{out} += t_{c,} \times h_{c}$
25.  else
26.     $\text{out} += t_{c,} \times \text{R}_{c}$
27.  end if
28.  $m \leftarrow \text{cumul} < 1 - \epsilon$  \quad $\triangleright$ Update mask
29. end for
30. return $\text{out}$, $\rho = \frac{\text{sum}(\rho)}{K}$

...to stabilize convergence during stochastic pondering [1]. To this end, we define a halting score distribution:

$$\mathcal{H} := \left[\frac{\sum_{k=1}^{K} h_{k}^{1}}{K}, \frac{\sum_{k=1}^{K} h_{k}^{2}}{K}, \ldots, \frac{\sum_{k=1}^{K} h_{k}^{L}}{K}\right],$$ (11)

that averages expected halting score for all tokens across at each layer of network (i.e., $\mathcal{H} \in \mathbb{R}^{L}$). Using this as an estimate of how halting likelihoods distribute across layers, we regularize this distribution towards a pre-defined prior using KL divergence. We form the new distributional prior regularization term as:

$$\mathcal{L}_{\text{distr.}} = \text{KL}(\mathcal{H} \mid | \mathcal{H}_{\text{target}}),$$ (12)

where KL refers to the Kullback-Leibler divergence, and $\mathcal{H}_{\text{target}}$ denotes a target halting score distribution with a guiding stopping layer. We use the probability density function of Gaussian distribution to define a bell-shaped distribution $\mathcal{H}_{\text{target}}$ in this paper, centered at the expected stopping depth $N_{\text{target}}$. Intuitively, this weakly encourages the expected sum of halting score for each token to trigger exit condition at $N_{\text{target}}$. This offers enhanced control of expected remaining compute, as we show later in experiments.

Our final loss function that trains the network parameters for adaptive token computation is formulated as:

$$\mathcal{L}_{\text{overall}} = \mathcal{L}_{\text{task}} + \alpha_{d}\mathcal{L}_{\text{distr.}} + \alpha_{p}\mathcal{L}_{\text{ponder}},$$ (13)

where $\alpha_{d}$ is a scalar coefficient that balances the distribution regularization against other loss terms.

4. Experiments

We evaluate our method for the classification task on the large-scale 1000-class ImageNet ILSVRC 2012 dataset [8] at 224 × 224 pixels. We first analyze the performance of adaptive tokens, both qualitatively and quantitatively. Then, we show the benefits of the proposed method over prior art, followed by a demonstration of direct throughput improvements of vision transformers on legacy hardware. Finally, we evaluate the different components of our proposed approach to validate our design choices.

**Implementation details.** We base AdaViT on the data-efficient vision transformer architecture (DeiT) [43] that includes 12 layers in total. Based on original training recipe¹, we train all models on only ImageNet1K dataset without auxiliary images. We use the default 16 × 16 patch resolution. For all experiments in this section, we use Adam for optimization (learning rate 1.5 · 10⁻³) with cosine learning rate decay. For regularization constants we utilize $\alpha_{d} = 0.1, \alpha_{p} = 5 \cdot 10^{-4}$ to scale loss terms. We use $\gamma = 5, \beta = -10$ for sigmoid control gates $H(\cdot)$, shared across all layers. We use the embedding value at index $e = 0$ to represent the halting probability ($H(\cdot)$) for tokens. Starting from publicly available pretrained checkpoints, we fine-tune DeiT-T/S variant models for 100 epochs, respectively, to learn adaptive tokens without distillation. We denote the associated adaptive versions as AdaViT-T/S respectively. In what follows, we mainly use the AdaViT-T for ablations and analysis before showing efficiency improvements for both variants afterwards. We find that mixup is not compatible with adaptive inference, and we focus on classification without auxiliary distillation token – we remove both from finetuning. Applying our finetuning on the full DeiT-S and DeiT-T results in a top-1 accuracy of 78.9% and 71.3%, respectively. For each training run we use 8 NVIDIA V100 GPUs and automatic-mixed precision (AMP) [33] acceleration.

¹Based on official repository at https://github.com/facebookresearch/DeiT.
4.1. Analysis

**Qualitative results.** Fig. 3 visualizes the tokens’ depth that is adaptively controlled during inference with our AdaViT-T over the ImageNet1K validation set. Remarkably, we observe that our adaptive token halting enables longer processing for highly discriminative and salient regions, often associated with the target class. Also, we observe a highly effective halting of relatively irrelevant tokens and their associated computations. For example, our approach on animal classes retains the eyes, textures, and colors from the target object and analyze them in full depth, while using fewer layers to process the background (e.g., the sky around the bird, and ocean around sea animals). Note that even background tokens marked as not important still actively participate in classification during initial layers. In addition, we also observe the inspiring fact that adaptive tokens can easily (i) keep track of repeating target objects, as shown in the first image of the last row in Fig. 3, and (ii) even shield irrelevant objects completely (see second image of last row).

**Token depth distribution.** Given a complete distinct token distribution per image, we next analyze the dataset-level token importance distributions for additional insights. Fig. 4 depicts the average depth of the learnt tokens over the validation set. It demonstrates a 2D Gaussian-like distribution that is centered at the image center. This is consistent with the fact that most ImageNet samples are centered, intuitively aligning with the image distribution. As a result, more compute is allocated on-the-fly to center areas, and computational cost on the sides is reduced.

**Halting score distribution.** To further evaluate the halting behavior across transformer layers, we plot the average layerwise halting score distribution over 12 layers. Fig. 5 shows box plots of halting scores averaged over all tokens per layer per image. The analysis is performed on 5K randomly sampled validation images. As expected, the halting score...
gradually increases at initial stages, peaks and then decreases for deeper layers.

**Easy and hard samples.** We can analyse the difficulty of an image for the network by looking at the averaged depth of the adaptive tokens per image. Therefore, in Fig. 6, we depict hard and easy samples in terms of the required computation. Note, all samples in the figure are correctly classified, and only differ by the averaged token depth. Hard samples represent images with informative visual features distributed over the entire image, and hence incur more computation.

**Class-wise sensitivity.** Given an adaptive inference paradigm, we analyze the change in classification accuracy for various classes with respect to the full model. In particular, we compute class-wise validation accuracy changes before and after applying adaptive inference. We summarize both qualitative and quantitative results in Table 1. We observe that originally very confident or uncertain samples are not affected by adaptive inference. Adaptive inference improves accuracy of the visually dominant classes such as individual furniture and animals.

| Rank | Class-wise Sensitivity to Adaptive Inference | Fixed acc. (act. rect.) | Adaptive acc. (act. rect.) |
|------|---------------------------------------------|------------------------|----------------------------|
| 1    | throne                                      | 74%                    | 56%                        |
| 2    | muzzle                                     | 62%                    | 80%                        |
| 3    | yellow lady slipper                         | 100%                   | 100%                       |
| 4    | lakeland terrier                            | 68%                    | 78%                        |
| 5    | sewing machine                              | 46%                    | 64%                        |
| 6    | velvet                                      | 14%                    | 10%                        |
| 7    | proboscis monkey                            | 38%                    | 58%                        |
| 8    | african elephant                            | 28%                    | 60%                        |
| 9    | cogi                                        | 20%                    | 60%                        |
| 10   | vacuum                                      | 40%                    | 40%                        |

Table 1. Ranking of stable and sensitive classes to the adaptive computation for tokens in AdaViT as compared to fixed computation graph that executes the full model for inference. Sample images are included for top three classes that favor or remain sensitive to adaptive computation.

### 4.2. Comparison to Prior Art

Next, we compare our method with previous work that study adaptive computation. For comprehensiveness, we systematically compare with five state-of-the-art halting mechanisms, covering both vision and NLP methods that tackle the dynamic inference problem from different perspectives:

- (i) adaptive computation time [17] as ACT reference applied on halting entire layers,
- (ii) confidence-based halting [31] that gauges on logits,
- (iii) similarity-based halting [12] that oversees layer-wise similarity,
- (iv) pondering-based halting [1] that exits based on stochastic halting-probabilities,
- (v) the very recent DynamicViT [36] that learns halting decisions via Gumble-softmax relaxation.

**Performance comparison.** We compare our results in Table 2 and demonstrate simultaneous performance improvements over prior art in having smaller averaged depth, smaller number of FLOPs and better classification accuracy. Notably our method involves no extra parameters, while cut-
To further visualize improvements over the state-of-the-art, our distributional prior allows us to better guide the expected token depth towards a target average depth, as seen in Fig. 8. As opposed to \( \alpha_p \) that indirectly gauges on the remaining efficiency and usually suffers from over-/under-penalization, our distributional prior guides a quick convergence to a target depth level, and hence improves final accuracy.

**“Free” embedding to learn halting.** Next we justify the usage of a single value in the embedding vector for halting score computation and representation. In the embedding vectors, we set one entry at a random index to zero and analyze the associated accuracy drop without any fine-tuning of the model. Repeating 10 times for DeiT-T/S variants, the ImageNet1K top-1 accuracy only drops by 0.08% ± 0.04%/0.04% ± 0.03%, respectively. This experiment demonstrates that one element in the vector can be used for another task with minimal impact on the original performance. In our experiments, we pick the first element in the vector and use it for the halting score computation.

**5. Limitations & Future Directions**

In this work we primarily focused on the classification task. However, extension to other tasks such as video processing can be of great interest, given not only spatial but also temporal redundancy within input tokens.

**6. Conclusions**

We have introduced AdaViT to adaptively adjust the amount of token computation based on input complexity. We demonstrated that the method improves vision transformer throughput on hardware without imposing extra parameters or modifications of transformer blocks, outperforming prior dynamic approaches. Captured token importance distribution adaptively varies by input images, yet coincides surprisingly well with human perception, offering insights for future work to improve vision transformer efficiency.

**Figure 8.** Training curves with (blue) and without (yellow) distributional priors towards a target depth of 9 layers. Both lines share the exact same training hyper-parameter set with the only difference in including the distributional prior guidance. As opposed to \( \alpha_p \) that over-penalizes the networks, \( L_{\text{dist}} \) guides a very fast convergence towards the target depth and yields a 6.4% accuracy gain.
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Appendix A - More Examples

Figure 9. Additional examples across a more diverse set of image categories – original image (left) and the dynamic token depth (right) of AdaViT-T on the ImageNet-1K validation set. Again adaptive tokens can quickly cater to informative regions while filtering out complex backgrounds, e.g., completely ignoring human faces and focusing on the coats, see the first two image on the first row. Even for a very small informative region of the target object, the computation can still be effectively allocated towards it, see the first golf-cart class sample of the last row as an example.
Appendix B - Additional Details

Training. For training setup other than the scaling constants, $lr$ specified in the main manuscript, we follow original repository for all other hyper-parameters at https://github.com/facebookresearch/DeiT such as dropout rate, momentum, preprocessing, etc, imposing minimum training recipe changes when adapting a static model to its adaptive counterpart.

Latency. We measure the latency on an NVIDIA TITAN RTX 2080 GPU with PyTorch for batch size of 64 images, CUDA 10.2. For GPU warming up, 100 forward passes are conducted, and then the median speed of the 1K measurements of the full model latency are reported. The exact same setup is shared across all baseline and proposed methods for a fair comparison.