BOOSTING ADVERSARIAL TRANSFERABILITY USING DYNAMIC CUES

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ABSTRACT

The transferability of adversarial perturbations between image models has been extensively studied. In this case, an attack is generated from a known surrogate *e.g.*, the ImageNet trained model, and transferred to change the decision of an unknown (black-box) model trained on an image dataset. However, attacks generated from image models do not capture the dynamic nature of a moving object or a changing scene due to a lack of temporal cues within image models. This leads to reduced transferability of adversarial attacks from representation-enriched *image* models such as Supervised Vision Transformers (ViTs), Self-supervised ViTs (*e.g.*, DINO) and Vision-language models (*e.g.*, CLIP) to black-box *video* models. In this work, we induce dynamic cues within the image models without sacrificing their original performance on images. To this end, we optimize *temporal prompts* through frozen image models to capture motion dynamics. Our temporal prompts are the result of a learnable transformation that allows optimizing for temporal gradients during an adversarial attack to fool the motion dynamics. Specifically, we introduce spatial (image) and temporal (video) cues within the same source model through task-specific prompts. Attacking such prompts maximizes the adversarial transferability from image-to-video and image-to-image models using the attacks designed for image models. As an example, an iterative attack launched from image model Deit-B with temporal prompts reduces generalization (top1 % accuracy) of a video model by 35% on Kinetics-400. Our approach also improves adversarial transferability to image models by 9% on ImageNet w.r.t the current state-of-the-art approach. Our attack results indicate that the attacker does not need specialized architectures, *e.g.*, divided space-time attention, 3D convolutions, or multi-view convolution networks for different data modalities. Image models are all we need to optimize for an effective surrogate and an adversarial attack to fool black-box models in a changing environment over time. Our code will be made public.

1 INTRODUCTION

Deep learning models are vulnerable to imperceptible changes to the input images. It has been shown that for a successful attack, an attacker no longer needs to know the attacked target model to compromise its decisions (Naseer et al., 2019; Nakka & Salzmann, 2021). Adversarial perturbations suitably optimized from a known source model (a surrogate) can fool an unknown target model (Kurakin et al., 2016). These attacks are known as black-box attacks since the attacker is restricted to access the deployed model or compute its adversarial gradient information. Adversarial attacks are continuously evolving, revealing new blind spots of deep neural networks.

Adversarial transferability has been extensively studied in image-domain (Wang & He, 2021; Naseer et al., 2022; Aich et al., 2022; Akhtar & Mian, 2018). Existing works demonstrate how adversarial patterns can be generalized to models with different architectures (Zhou et al., 2018) and even different data domains (Naseer et al., 2019). However, the adversarial transferability between different architecture families designed for varying data modalities, *e.g.*, image models to video models, has not been actively explored. Since the adversarial machine learning topic has gained maximum attention in the image-domain, it is natural to question if image models can help transfer better to video-domain models. However, the image models lack dynamic temporal cues which are essential for transfer to the video models.

We are motivated by the fact that in a real-world setting, a scene is not static but mostly involves various dynamics, *e.g.*, object motion, changing viewpoints, illumination and background changes. Therefore, exploiting *dynamic cues* within an adversarial attack is essential to find blind-spots of unknown target models. For this purpose, we introduce the idea of encoding disentangled temporal representations within an image-based Vision Transformer (ViT) model using dedicated *temporal prompts* while keeping the remaining network frozen. The temporal prompts can learn the dynamic cues which are exploited during attack for improved transferability from image-domain models. Specifically, we introduce the proposed temporal prompts to three types of image models with enriched representations acquired via supervised (ViT (Dosovitskiy et al., 2020)), self-supervised (DINO (Caron et al., 2021)) or multi-modal learning (CLIP (Radford et al., 2021)).

Our approach offers the benefit that the attacks do not need to rely on specialized networks designed for videos towards better adversarial transferability. As an example, popular model designs for videos incorporate 3D convolutions, space-time attention, tube embeddings or multi-view information to be robust against the temporal changes (Bertasius et al., 2021; Arnab et al., 2021). Without access to such specific design choices, our approach demonstrates how an attacker can leverage regular image models augmented with temporal prompts to learn dynamic cues. Such dynamic cues are shown here to aid in better transfer not only to video models, but also to the original domain (image) models due to the expressivity of dynamic information. Further, our approach can be easily extended to image datasets, where disentangled representations can be learned via tokens across a scale-space comprising of varying image resolutions. In summary, the major contributions of this work include:

- We demonstrate how temporal prompts incorporated with frozen image-based models can help model dynamic cues which can be exploited to fool deep networks designed for videos.
- Our approach for dynamic cue modeling via prompts does not affect the original spatial representations learned by the image-based models during pre-training, *e.g.*, fully-supervised, self-supervised and multimodal models.
- The proposed method significantly improves transfer to black-box image and video models. Our approach is easily extendable to 3D datasets via learning cross-view prompts; and image-only datasets via modeling the scale-space. Finally, it enables generalization from popular plain ViT models without considering video-specific specialized designs.

We analyse the adversarial space of three type of image models (fully-supervised, self-supervised, and text-supervised). A pre-trained ImageNet ViT with only 5 million parameters exhibits 44.6 and 72.2 top-1 (%) accuracy on Kinetics-400 and ImageNet validation sets using our approach, thereby significantly improves the adversarial transferability on video-domain models. A similar trend exists on other image models. Our results indicate that the multimodal CLIP can better adapt to video modalities than fully-supervised or self-supervised ViTs. However, CLIP adversaries are relatively less transferable as compared to fully-supervised ViT or self-supervised DINO model. As an example, a momentum based iterative attack launched from our DINO model can reduce the performance of TimesFormer (Bertasius et al., 2021) from 90.6% to 45.2% on UCF dataset.

2 Related Work

Adversarial Attacks: Transferable adversarial attacks compromise the decision of a black-box target model. Attacker can not access weights, model outputs or gradient information of a black-box model. These attacks can broadly be categorized into iterative (Goodfellow et al., 2014; Dong et al., 2018; Lin et al., 2019; Wang & He, 2021; Xie et al., 2019; Zhou et al., 2018; Naseer et al., 2022) and generative (Poursaeed et al., 2018; Naseer et al., 2019; 2021; Aich et al., 2022) methods. Iterative attacks optimize adversary from a given clean sample by searching adversarial space of a white-box surrogate model iteratively. Attacker can access weights, model outputs and gradient information of a white-box surrogate model. Generative attacks on the other hand train a universal function (an auto-encoder) against the white-box model over a given data distribution. These attacks can generate adversary via single forward-pass after training. Our proposed approach can be augmented with any of these existing attacks to boost transferability from image-to-video or multi-view models.

Prompt Adaptation of Image Models: Prompting refers to providing manual instructions (Liu et al., 2021a; Jiang et al., 2020; Shin et al., 2020) or fine-tuning task-specific tokens (Li & Liang, 2021; Liu et al., 2021b; Lester et al., 2021) for a desired behavior from large language models (*e.g.*,

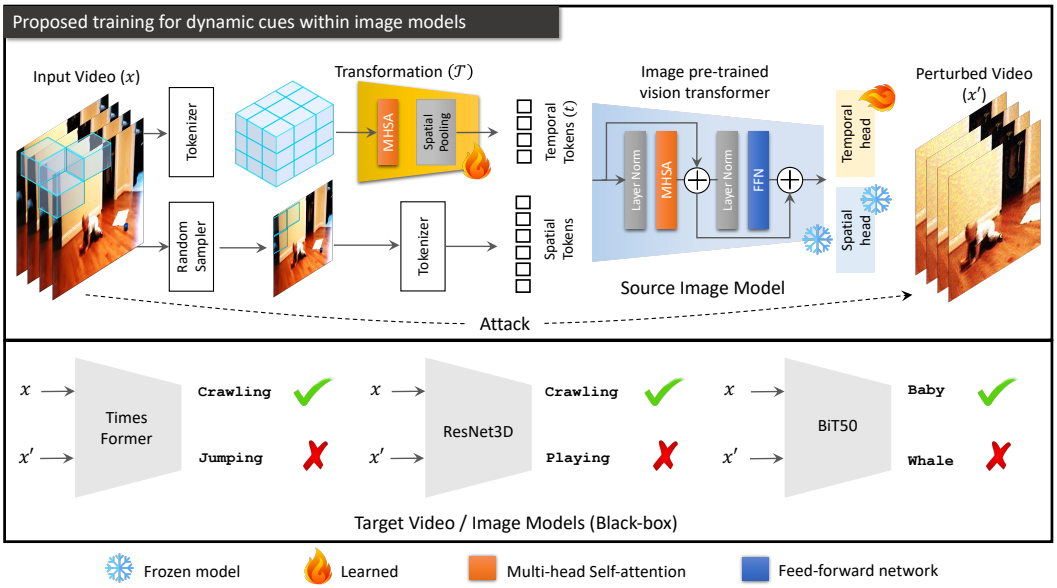

Figure 1: **Overview of inducing dynamic cues within image models:** Attackers can easily access freely available, pre-trained image models learned on large-scale image and language datasets to launch adversarial attacks. These models, however, lack temporal information. Therefore, adversarial attacks launched using image models have less success rate against a *moving target* such as in videos. We learn a transformation $\mathcal{T}(.)$ to convert a given video with t number of frames into t temporal tokens. Our transformation is based on self-attention thus it learns the motion dynamics between the video frames with global context during training. We randomly sample a single frame to represent the spatial tokens. The temporal and spatial tokens are concatenated and passed through the frozen model. The spatial tokens are ignored while the average of temporal tokens is processed through a temporal head for video recognition. The image/spatial class token learned on images (*e.g.*, ImageNet) interacts with our temporal tokens (*e.g.*, Kinetics) within the network through self-attention. After the training, image and video solutions are preserved within the spatial and temporal tokens and used in adversarial attacks.

GPT-3). Recently, prompt fine-tuning has been studied for vision models with promising results to adapt image models from one image task to another (Jia et al., 2022; Elsayed et al., 2018). We extend prompt transfer learning to adapt image models to videos and multi-view data modalities. We only train a transformation along with a prompt class token to learn dynamic cues and adapt image model to video tasks. Our approach allows transferable attacks from image-to-video or multi-view models.

3 Boosting Adversarial Transferability using Dynamic Cues

Adversarial transferability refers to manipulating a clean sample (image, video, or 3D object rendered into multi-views) in a way that is deceiving for an unknown (black-box) model. In the absence of an adversarial perturbation, the same black-box model predicts the correct label for the given image, video, or a rendered view of a 3D object. A known surrogate model is usually used to optimize for the adversarial patterns. Instead of training the surrogate model from scratch on a given data distribution, an attacker can also adapt pre-trained image models to the new task. These image models can include supervised ImageNet models such as Deit (Touvron et al., 2020), self-supervised ImageNet models like DINO (Caron et al., 2021), and text-supervised large-scale multi-modal models *e.g.* CLIP (Radford et al., 2021). The adversarial attack generated from such pre-trained models with enriched representations transfer better in the black-box setting for image-to-image transfer task (Zhang et al., 2022; Naseer et al., 2022; Aich et al., 2022). However, adversarial perturbations optimized from image models are not well suited to fool motion dynamics learned by a video model (Sec. 4). To cater for this, we introduce temporal cues to model motion dynamics within adversarial attacks through pre-trained image models. Our approach, therefore, models both spatial and temporal information during the attack (Sec. 3.1) and does not depend on specialized video networks *e.g.*, with 3D convolutions (Tran et al., 2018), space-time divided attention (Bertasius et al., 2021) or even multi-branch models (Su et al., 2015). To this end, we first introduce *temporal prompt adaptation* of

image models to learn dynamic cues on videos or multi-view information on rendered views of a 3D object, as explained next.

3.1 Introducing Dynamic Cues through Temporal Prompts

Consider an image model $\mathcal{F}$ pre-trained on the input samples $\boldsymbol{x}$ of size $c \times h \times w$, where c, h and w represent the color channels, height and width, respectively. In the case of Vision Transformer (Dosovitskiy et al., 2020; Touvron et al., 2020), such input samples are usually divided into equally sized N patch tokens of dimension D. The patch tokens combined with the class token[1] $\mathcal{I}_{cls} \in \mathbb{R}^{1\times D}$, processed by multiple multi-head self-attention (MHSA) blocks before passing the $\mathcal{I}_{cls}$ through the task specific head MLP. The spatial class token in image models, $\mathcal{I}_{cls}$, is never optimized for temporal information. Our objective is to adapt the image model for videos or multi-views through temporal class token $\mathcal{I}^t_{cls}$ that is optimal for input samples of size $t \times c \times h \times w$, where t represents the number of temporal frames in a video or rendered views of a 3D object.

A trivial way is to concatenate all the additional frames of a video to generate $t \times N$ patch tokens. We can then optimize temporal class token $\mathcal{I}^t_{cls}$ using prompt learning (Jia et al., 2022) and incorporate the dynamic cues within an image model. This approach, however, has a drawback as the computational time complexity increases significantly to $\mathcal{O}\left((t \times N)^2 \times D\right)$ within the self-attention layers. Another naive way is to either apply temporal pooling to convert $t \times N$ to only N spatial tokens or approximate a video via a single frame that is $t_i \times c \times h \times w$, where t_i corresponds to a randomly sampled frame from the input video. These approaches result in a sub-optimal attack as we are unable to optimize for motion dynamics available from different video frames.

Our approach is described in Fig 1. We induce the temporal information within image models without increasing the quadratic complexity within self-attention of a pre-trained and frozen ViT. Our approach preserves the original image or spatial representation encoded within spatial class token $\mathcal{I}_{cls}$ (Table 5). Both spatial and temporal tokens, $\mathcal{I}_{cls}$ and $\mathcal{I}^t_{cls}$, are then used within our attack approach (Sec. 3.2). We approximate a video with a single frame and simultaneously learn a Transformation $\mathcal{T}$ to generate temporal prompts to model temporal information, as explained next.

3.1.1 Temporal Prompts through Transformation

The learnable transformation $\mathcal{T}$ processes a video with t number of temporal frames and produces only t temporal prompts (Fig. 1). A video sample, $\boldsymbol{x}$, is divided into patch tokens such that $\boldsymbol{x} \in \mathbb{R}^{t\times N\times D}$. The transformation $\mathcal{T}$ is a single self-attention layer (Dosovitskiy et al., 2020) that interacts between the tokens and learns the relationship between the temporal frames. The transformation output is then pooled across spatial dimension N to produce t temporal tokens *i.e.*, $\mathcal{T}(\boldsymbol{x}) \in \mathbb{R}^{t\times D}$. Attacking such temporal tokens allows finding adversarial patterns capable of fooling the dynamic cues learned by the unknown black-box video model. **Mimicking dynamic behavior on image datasets:** Image samples are static and have no temporal dimension. So we adopt a simple strategy to mimic changing behavior for such static data. We consider images at different spatial scales to obtain a scale-space (Fig. 2) and model temporal prompts for image datasets. The dynamic cues within image models not only boost transferability of the existing adversarial attacks from image-to-video models but also increase the attack success rate in the black-box image models (Sec. 4).

3.1.2 Image Models with Temporal and Spatial Prompts

Our approach is motivated by the shallow prompt transfer learning (Jia et al., 2022). Given a video $\boldsymbol{x}$, we randomly sample a single frame $\boldsymbol{x}_i \sim \boldsymbol{x}$ and divide it into patch tokens such that $\boldsymbol{x}_i \in \mathbb{R}^{N\times D}$. These patch tokens are then concatenated with the temporal prompts generated by $\mathcal{T}(\boldsymbol{x})$, a temporal class token $\mathcal{I}^t_{cls}$, and the image class token $\mathcal{I}_{cls}$ to equip the pre-trained image representation of a model $\mathcal{F}$ with discriminative temporal information:

$$\mathcal{F}(\boldsymbol{x}) = \mathcal{F}\left(\left[\mathcal{I}^t_{cls}, \mathcal{T}(\boldsymbol{x}), \mathcal{I}_{cls}, \boldsymbol{x}_i\right]\right) \tag{1}$$

The average of refined temporal class tokens, and t temporal prompts generated by $\mathcal{T}$ is then projected through the temporal MLP head for the new video task. For the sake of brevity, we will refer to the

[1]Hierarchical ViTs such as Swin Transformer (Liu et al., 2021c) or more simple designs without self-attention layers like MLP-Mixer (Tolstikhin et al., 2021) use average of patch tokens as the class token.

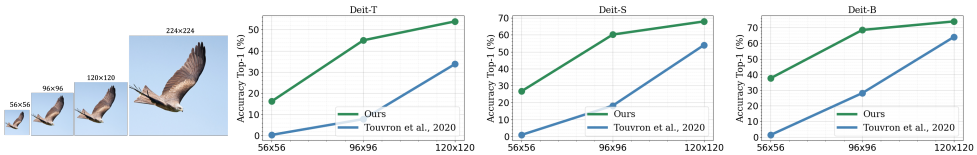

Figure 2: ***Mimicking dynamic cues on static images:*** We optimize our proposed transformation (Fig. 1) for different spatial scales to mimic changes. This improves model generalization *e.g.* Deit-T performance increases from 7.7% to 45% on ImageNet val. set at 96×96. Attacking models with such prompts increases transferability.

average of our temporal class and prompts tokens collectively as $\mathcal{I}_{cls}^{tp}$. **Training:** Given a pre-trained ViT, we freeze all of its existing weights and insert our learnable transformation ($\mathcal{T}$), temporal class token $\mathcal{I}_{cls}^{t}$, and video-specific MLP head. We train for 15 epochs only using SGD optimizer with a learning rate of 0.005 which is decayed by a factor of 10 after the 11th and 14th epoch. We use batch size of 64 and train on 16 A100 GPUs for large-scale datasets such as Kinetics-400 (Kay et al., 2017) and only 2 A100 GPUs for other small datasets. We discuss the effect of our temporal prompts on temporal (video) and spatial (image) solutions in Table 5. Our method mostly retains the original image solution captured in image class token $\mathcal{I}_{cls}$ while exhibiting dynamic temporal modeling.

3.2 Transferable Attack using Spatial and Temporal Cues

Given an image model $\mathcal{F}$ adapted for motion dynamics via our approach (Fig. 1), our attack exploits the spatial and temporal cues to generate transferable perturbations for both image and video models.

- *Given a video and its corresponding label:* Our attack uses temporal class tokens $\mathcal{I}_{cls}^{tp}$ in a supervised manner, while the spatial class token $\mathcal{I}_{cls}$ serves in an unsupervised objective.
- *Given an image and its corresponding label:* Our attack uses temporal class tokens $\mathcal{I}_{cls}^{tp}$ learned at different resolutions to mimic the dynamic behavior from image dataset in a supervised manner, while the spatial class token $\mathcal{I}_{cls}$ serves in an unsupervised objective.

We generate an adversarial example $\boldsymbol{x'}$ for a video or image sample $\boldsymbol{x}$ using the following objective:

$$\text{find } \boldsymbol{x'} \text{ such that } \mathcal{F}(\boldsymbol{x'})_{argmax} \neq y, \quad \text{and } \|\boldsymbol{x} - \boldsymbol{x'}\|_p \leq \epsilon, \tag{2}$$

where y is the original label and ϵ represents a maximum perturbation budget within a norm distance p. We optimize Eq. 2 by maximizing the loss objective in Eq. 3 within existing adversarial attacks.

$$\text{maximize } \mathcal{L} = \mathcal{L}_s - \mathcal{L}_{ss}, \tag{3}$$

where $\mathcal{L}_s$ is a supervised loss function. It uses the labels of a given image/video through supervised MLP head. $\mathcal{L}_s$ can be optimized by any of the existing supervised losses proposed in transferable attacks literature; cross-entropy (Dong et al., 2018), relativistic cross-entropy (Naseer et al., 2019), or logit loss (Zhao et al., 2021). Unless otherwise mentioned, we use cross-entropy loss to demonstrate the effectiveness of our approach. Similarly, $\mathcal{L}_{ss}$ is self-supervised loss that exploits pre-trained representation within spatial class tokens. We minimize the cosine similarity between the class tokens of clean and adversarial samples. In this manner, any of the existing attacks can be combined with our approach to transfer adversarial perturbations as we demonstrate in Sec. 4.

3.2.1 Changing Spatial Resolution for Regularization

An adversarial attack can easily overfit the source models meaning it can have a 100% success rate on the source model but mostly fails to fool the unknown black-box model. Different heuristics like adding momentum (Dong et al., 2018; Lin et al., 2019; Wang & He, 2021), augmentations (Naseer et al., 2021; Xie et al., 2019), ensemble of different models (Dong et al., 2018) or even self-ensemble (Naseer et al., 2022) at a target resolution are proposed to reduce such overfitting and increase adversarial transferability. Low-resolution pre-training followed by high-resolution fine-tuning have a regularization effect on the generalization of neural networks (Touvron et al., 2022). Similarly, we observe that fine-tuning temporal prompts for motion dynamics at low resolution (e.g., 96×96) within a model pre-trained on high resolution (224×224) also has a complimentary regularization effect on the transferability of adversarial perturbations (Tables 3 and 4). Most publicly available image models are trained at a resolution of size 224×224 and their performance at low-resolution

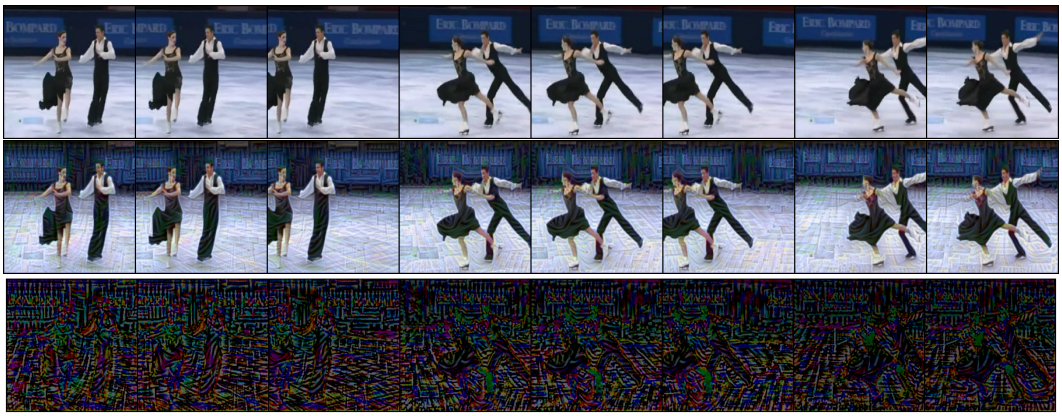

Figure 3: ***Visualizing the behavior of Adversarial Patterns across Time:*** We generate adversarial signals from our DINO model with temporal prompts using DIM attack (Xie et al., 2019). Observe the change in gradients across different frames (*best viewed in zoom*). We provide visual demos of adversarial patterns in Appendix C.

inputs is sub-optimal (Fig. 2). Learning at low-resolution with our approach (Fig. 1) also allows to mimic a changing scene over time from static datasets like ImageNet (Fig. 2). Our low-resolution temporal prompts (Sec. 3.1) significantly improves generalization at low-resolution inputs (Fig. 2).

4 EXPERIMENTS

We generate l_∞ adversarial examples from the adapted image models and study their transferability to video and image models. The maximum pixel perturbation is set to $\epsilon \leq 16$ for pixel range of [0, 255]. We use standard image attacks to optimize adversarial examples through our adapted image models and boost adversarial transferability to video models by using the following protocols:

Surrogate image models: We optimize adversaries from the known surrogate models. We study three types of surrogate image models trained via supervised (Touvron et al., 2020), self-supervised (Caron et al., 2021) and text-supervised (Radford et al., 2021) models.

$-$*Supervised image models:* We use Deit-T, DeiT-S, and DeiT-B with 5, 22, and 86 million parameters to video datasets. These models are pre-trained in a supervised manner on ImageNet.

$-$*Self-Supervised image model:* We use Vision Transformer trained in self-supervised fashion on ImageNet using DINO training framework (Caron et al., 2021).

$-$*Text-Supervised image model:* We adopt CLIP image encoder only trained on text-guided images.

DeiT-B, DINO, and CLIP share the same network based on Vision Transformer. These models process images of size $3\times224\times224$ that are divided into 196 patches with a patch size of 16. Each of these patch tokens has 768 embedding dimensions. Thus, the only difference between these models lies in their corresponding training frameworks. These models are adapted to different video datasets. Adversarial examples are then simply created using existing single and multi-step attacks (Goodfellow et al., 2014; Madry et al., 2018; Dong et al., 2018; Xie et al., 2019).

Target video and image models: We transfer adversarial examples to unknown (black-box) video and image models. $-$*Target Video Models:* We consider recently proposed TimesFormer (Bertasius et al., 2021) with divided space-time attention, 3D convolutional network (Tran et al., 2018), and multi-view convolutional network (Su et al., 2015). $-$*Target Image Models:* We consider the same image models used in baseline by (Naseer et al., 2022): BiT-ResNet50 (BiT50) (Beyer et al., 2021), ResNet152 (Res152) (He et al., 2016), Wide-ResNet-50-2 (WRN) (Zagoruyko & Komodakis, 2016), DenseNet201 (DN201) (Huang et al., 2017) and other ViT models including Token-to-Token transformer (T2T) (Yuan et al., 2021), Transformer in Transformer (TnT) (Mao et al., 2021).

Adapting image models for videos using dynamic cues: We use UCF (Soomro et al., 2012), HMDB (Kuehne et al., 2011), K400 (Kay et al., 2017), and SSv2 (Goyal et al., 2017) training sets to learn temporal prompts and adapt image models to videos via our approach (Fig.1). HMDB has the smallest validation set of 1.5k samples. For evaluating robustness, we selected all validation samples in HMDB, while randomly selected 1.5k samples from UCF, K400, and SSv2 validation sets.

Models (↓)	Temporal Prompts	TimesFormer UCF	TimesFormer HMDB	TimesFormer K400	TimesFormer SSv2	ResNet3D UCF	ResNet3D HMDB	ResNet3D K400	ResNet3D SSv2	MVCNN Depth	MVCNN Shaded
Fast Gradient Sign Method (FGSM) (Goodfellow et al., 2014)											
		90.6	59.1	75.6	45.1	79.9	45.4	60.5	26.7	92.6	94.8
Deit-T	✗	75.1	32.9	57.8	23.5	25.7	9.8	23.3	14.7	16.0	79.0
	✓	64.5 (-26.1)	21.9 (-37.2)	51.6 (-24.0)	19.8 (-25.3)	22.3 (-57.6)	8.9 (-36.5)	19.4 (-41.1)	13.9 (-12.8)	15.2 (-77.4)	77.4 (-17.4)
Deit-S	✗	74.7	33.5	58.2	23.0	25.4	9.7	23.9	15.9	17.2	79.8
	✓	64.0 (-26.6)	20.6 (-38.5)	48.5 (-27.1)	19.1 (-26.0)	22.6 (-57.3)	8.6 (-36.8)	20.6 (-39.9)	13.6 (-13.1)	15.9 (-76.7)	78.9 (-15.9)
Deit-B	✗	75.5	31.7	57.5	22.6	25.0	9.2	22.4	15.5	17.3	80.6
	✓	64.7 (-25.9)	20.0 (-39.1)	48.6 (-27.0)	19.3 (-25.8)	22.7 (-57.2)	8.1 (-37.3)	19.5 (-41.0)	13.4 (-13.3)	17.1 (-75.5)	80.9 (-13.9)
DINO	✗	71.0	33.7	54.2	23.8	32.0	12.4	24.3	15.2	15.2	72.7
	✓	60.7 (-29.9)	18.8 (-40.3)	46.7 (-28.9)	19.4 (-25.7)	21.9 (-58.0)	8.3 (-37.1)	19.6 (-40.9)	13.9 (-12.8)	15.0 (-77.6)	70.7 (-24.1)
CLIP	✗	79.8	36.6	62.3	26.4	38.5	15.0	29.9	17.3	15.8	81.4
	✓	77.5 (-13.1)	29.3 (-29.8)	59.5 (-16.1)	25.0 (-20.1)	35.6 (-44.3)	11.2 (-34.2)	28.8 (-31.7)	16.5 (-10.2)	15.6 (-77.0)	81.2 (-13.6)
Projected Gradient Decent (PGD) (Madry et al., 2018)											
Deit-T	✗	84.9	40.9	68.3	32.5	69.4	32.7	44.3	18.4	37.0	90.5
	✓	78.1 (-12.5)	32.0 (-27.1)	61.5 (-14.1)	27.8 (-17.3)	65.9 (-14.0)	29.5 (-15.9)	39.1 (-21.4)	17.6 (-9.1)	34.6 (-58.0)	90.2 (-4.6)
Deit-S	✗	85.1	42.0	68.6	32.5	69.9	32.7	44.8	19.4	39.4	90.9
	✓	74.1 (-16.5)	26.1 (-33.0)	58.3 (-17.3)	26.1 (-19.0)	65.4 (-14.5)	28.2 (-17.2)	28.9 (-31.6)	17.1 (-9.6)	36.5 (-56.1)	90.1 (-4.7)
Deit-B	✗	85.5	41.5	67.7	33.3	69.9	32.6	44.7	18.9	37.7	91.1
	✓	73.6 (-17.0)	25.0 (-34.1)	56.3 (-19.3)	24.4 (-20.7)	64.7 (-15.2)	26.6 (-18.8)	37.0 (-23.5)	16.6 (-10.1)	36.7 (-55.9)	90.5 (-4.3)
DINO	✗	81.7	38.0	64.8	30.9	68.0	31.8	42.5	18.2	33.1	89.2
	✓	64.9 (-25.7)	14.8 (-44.3)	51.5 (-24.1)	22.4 (-22.7)	63.1 (-16.8)	25.9 (-19.5)	35.2 (-25.3)	16.6 (-10.1)	28.9 (-63.5)	87.5 (-7.3)
CLIP	✗	86.9	44.5	70.7	35.4	71.9	35.1	46.5	20.0	39.8	91.3
	✓	82.6 (-8.0)	32.3 (-26.8)	66.9 (-8.7)	32.7 (-12.4)	69.7 (-10.2)	28.9 (-16.5)	43.2 (-17.3)	18.9 (-7.8)	37.6 (-55.0)	90.1 (-4.7)

Table 1: ***Adversarial Transferability from image to video models:*** Adversarial accuracy (%) is reported at $\epsilon \leq 16$. When attack is optimized from an image model without temporal prompts (✗), then we minimize the unsupervised adversarial objective (Eq. 3) i.e., cosine similarity between the feature embedding of spatial class token of clean and adversarial frames. We use 8 frames from a given video. Attacks transferability improves by a clear margin with temporal prompts. Clean accuracy (top1 % on randomly selected validation set of 1.5k samples) is highlighted with cell color. *Single step FGSM and multi-step PGD attacks perform better with our proposed temporal prompts (*e.g. *FGSM reduces TimesFormer generalization from 90.6% to 64.5% on UCF by exploiting dynamic cues within the DeiT-T). A similar trend exists for ResNet3D and MVCNN.*

We also use mult-view training samples rendered for 3D ModelNet40 (depth and shaded) for image models. We use validation samples of rendered mult-views for both modalities.

Adapting image models to images mimicking dynamic cues: We use ImageNet training set and learn our proposed transformation and prompts at multiple spatial scales; 56×56, 96×96, 120×120, and 224×224. We optimize adversarial attacks at the target resolution of 224×224 by using the ensemble of our transformation learned at multiple resolutions. We mimic the change over time by changing the spatial scale or resolution over time. We study our attack approach using the 5k samples from ImageNet validation set proposed by (Naseer et al., 2022).

Inference and metrics: We randomly sample 8 frames from a given video for testing. We report drop in top-1 (%) accuracy on adversarial and clean videos. We report fooling rate (% of adversarial samples for which the predicted label is flipped w.r.t the original labels) to evaluate on image datasets.

Extending image attacks to videos: We apply image attacks such as single step fast gradient sign method (FGSM) (Goodfellow et al., 2014) as well as iterative attacks including PGD (Madry et al., 2018), MIM (Dong et al., 2018) and input diversity (augmentations to the inputs) (DIM) (Xie et al., 2019) attacks to adapted image models and transfer their adversarial perturbations to black-box video models. We follow the default attack settings used by (Naseer et al., 2022). Our propose transformation ($\mathcal{T}(.)$) allows to model temporal gradients during attack optimization (Fig. 3).

4.1 Adversarial Transfer from Image-to-Video Models

The generalization of image models on videos is discussed in Table 5. We observe that image solution remains preserved in ViT backbones even after training with our proposed transformation and temporal prompts. Deit models retain their top-1 (%) accuracy on ImageNet when measured through image class token, while also exhibiting decent performance on video datasets and rendered

Models (↓)	Temporal Prompts	TimesFormer				ResNet3D				MVCNN	
		UCF	HMDB	K400	SSv2	UCF	HMDB	K400	SSv2	Depth	Shaded
Momentum Iterative Fast Gradient Sign Method (MIM) (Dong et al., 2018)											
		90.6	59.1	75.6	45.1	79.9	45.4	60.5	26.7	92.6	94.8
Deit-T	✗	77.0	30.1	58.5	25.2	42.0	16.2	29.1	16.0	19.2	83.0
	✓	66.9$_{(-23.7)}$	21.4$_{(-37.7)}$	51.4$_{(-24.2)}$	21.5$_{(-23.6)}$	41.5$_{(-38.4)}$	16.1$_{(-29.3)}$	26.4$_{(-34.1)}$	15.3$_{(-11.4)}$	19.0$_{(-73.6)}$	82.9$_{(-11.9)}$
Deit-S	✗	78.7	31.8	59.3	25.1	42.2	16.5	31.0	16.5	20.6	83.6
	✓	60.8$_{(-29.8)}$	16.1$_{(-43.0)}$	47.6$_{(-28.0)}$	21.0$_{(-24.1)}$	41.9$_{(-38.0)}$	15.7$_{(-29.7)}$	26.8$_{(-33.7)}$	14.2$_{(-12.5)}$	19.3$_{(-73.3)}$	83.5$_{(-11.3)}$
Deit-B	✗	78.7	32.0	59.7	25.9	43.1	16.2	29.5	16.8	20.6	84.4
	✓	61.7$_{(-25.9)}$	15.6$_{(-43.5)}$	45.2$_{(-30.4)}$	19.1$_{(-26.0)}$	40.7$_{(-39.2)}$	13.6$_{(-31.8)}$	24.8$_{(-35.7)}$	14.5$_{(-12.2)}$	20.5$_{(-72.1)}$	84.2$_{(-10.6)}$
DINO	✗	71.3	28.0	54.6	24.1	46.0	18.8	30.3	15.9	19.7	80.4
	✓	47.7$_{(-42.9)}$	8.40$_{(-50.7)}$	38.8$_{(-36.8)}$	16.4$_{(-28.7)}$	39.8$_{(-40.1)}$	12.7$_{(-32.7)}$	24.5$_{(-36.0)}$	14.3$_{(-12.4)}$	19.4$_{(-73.2)}$	80.7$_{(-14.1)}$
CLIP	✗	81.8	35.6	63.5	29.3	53.2	21.9	35.5	17.9	20.8	86.7
	✓	78.2$_{(-12.4)}$	28.2$_{(-30.9)}$	61.3$_{(-14.3)}$	27.2$_{(-17.9)}$	45.9$_{(-34.0)}$	17.8$_{(-27.6)}$	32.9$_{(-27.6)}$	16.5$_{(-10.2)}$	20.2$_{(-72.4)}$	84.7$_{(-10.1)}$
MIM with Input Diversity (DIM) (Xie et al., 2019)											
Deit-T	✗	75.3	28.2	59.2	24.3	41.3	16.5	29.5	16.3	20.3	84.5
	✓	62.6$_{(-28.0)}$	16.9$_{(-42.2)}$	48.1$_{(-27.5)}$	20.5$_{(-24.6)}$	37.8$_{(-42.1)}$	13.4$_{(-32.0)}$	24.2$_{(-36.3)}$	14.3$_{(-12.4)}$	19.6$_{(-73.0)}$	85.0$_{(-9.8)}$
Deit-S	✗	76.3	29.4	57.5	24.1	39.8	17.3	29.8	16.2	21.8	85.9
	✓	54.1$_{(-36.5)}$	12.3$_{(-46.8)}$	42.8$_{(-32.8)}$	17.7$_{(-27.4)}$	36.8$_{(-43.1)}$	12.7$_{(-32.7)}$	22.3$_{(-38.2)}$	14.6$_{(-12.1)}$	21.0$_{(-71.6)}$	85.7$_{(-9.1)}$
Deit-B	✗	75.9	28.8	57.8	24.5	41.5	16.5	30.5	15.6	22.2	85.1
	✓	55.5$_{(-35.1)}$	12.6$_{(-46.5)}$	40.6$_{(-35.0)}$	16.8$_{(-28.3)}$	37.3$_{(-42.6)}$	11.4$_{(-34.0)}$	21.5$_{(-39.0)}$	13.3$_{(-13.4)}$	20.5$_{(-72.1)}$	86.3$_{(-8.5)}$
DINO	✗	64.9	23.1	51.8	22.6	43.5	16.7	27.6	13.7	19.0	80.2
	✓	45.2$_{(-45.4)}$	7.30$_{(-51.8)}$	35.8$_{(-39.8)}$	15.8$_{(-29.3)}$	32.2$_{(-47.7)}$	10.6$_{(-34.8)}$	18.3$_{(-42.2)}$	12.0$_{(-14.7)}$	18.9$_{(-73.7)}$	78.6$_{(-16.2)}$
CLIP	✗	78.0	29.5	61.0	26.9	50.0	19.6	32.8	16.9	20.8	87.8
	✓	73.4$_{(-17.2)}$	22.7$_{(-36.4)}$	56.7$_{(-18.9)}$	25.1$_{(-20.0)}$	46.5$_{(-33.4)}$	13.6$_{(-31.8)}$	31.5$_{(-29.0)}$	15.7$_{(-11.0)}$	20.5$_{(-72.1)}$	87.4$_{(-7.4)}$

Table 2: ***Adversarial Transferability from image to video models:*** Adversarial accuracy (%) is reported at $\epsilon \leq 16$. When attack is optimized from an Image model without temporal prompts (✗), then we minimize the unsupervised adversarial objective (Eq. 3), cosine similarity, between the feature embedding of spatial class token of clean and adversarial frames. We use 8 frames from a given video. Attacks transferability improves by a clear margin with temporal prompts. Clean accuracy (top1 % on randomly selected validation set of 1.5k samples) is highlighted with cell color. *We observe that a small Image model (*e.g. *Deit-T with only 5 Million parameters) can significantly reduce the generalization of TimesFormer with the presence of our temporal prompts. The attack performance with temporal prompts increases with network capacity (*e.g. *Deit-T to Deit-B).*

Models (↓)	Method	Convolutional				Transformer			
		BiT50	Res152	WRN	DN201	ViT-L	T2T24	TnT	T2T-7
MIM with Input Diversity (DIM) (Xie et al., 2019)									
Deit-B	Naseer et al. (2022)	80.10	84.92	86.36	89.24	78.90	84.00	92.28	93.42
Deit-B	Ours	**86.64**	90.88	92.14	93.82	95.64	**95.74**	**98.48**	94.74
DINO		84.36	**93.74**	**95.16**	**96.20**	**96.48**	89.68	94.74	**96.18**
CLIP		55.34	64.24	65.76	71.78	59.94	54.66	62.72	75.80

Table 3: ***Adversarial Transferability from image to image models:*** Fool Rate (%) on 5k ImageNet val. samples from Naseer et al. (2022). We compare against the best results from Naseer et al. (2022) that our baseline is a self-ensemble Deit-B with token refinement blocks. To mimic the dynamics with static images, we optimize our proposed prompts at resolutions of 56×56, 96×94, 120×120, and 224×224. Adversaries are optimized at the target resolution of 224×224. Our method performs favorably well against self-ensemble with refined tokens.

Models	Temporal Prompts	SR	TimesFormer	
			UCF	HMDB
DeiT-B	✗	✗	75.9	28.8
	✓	✗	55.5	12.6
	✓	✓	**53.9**	**11.8**

Table 4: ***Effect of Change in Spatial Resolution (SR):*** Incorporating change in spatial resolution improves adversarial transferability. Adversaries are created at target resolution of 224 from an ensemble of models adopted at 56×56, 96×96, and 224×224.

mulit-views of ModelNet40. CLIP achieves the best performance on videos. The transferability of image based attacks from our adapted image models to video and multi-view models is presented in Tables 1 and 2. Following insights emerges from our analysis: **a)** The attack success to video models increases with size of the image models. The larger the image model (*e.g.* Deit-T to DeiT-B) the higher the attack success, **b)** The adversarial perturbations generated using self-supervised DINO

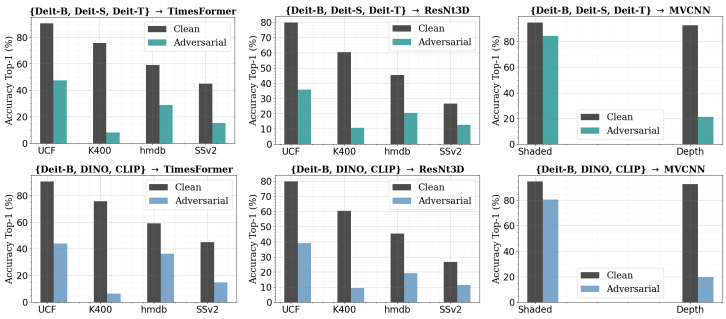

Figure 4: ***Effect of Ensemble Learning:*** Adversaries from an ensemble of adopted image models transfer well and fool the black-box video models with a high success rate. *First row* shows transferablity from an ensemble of different networks, while *second row* shows attack results from an ensemble of similar networks but pre-trained with different training schemes.

Models	ImageNet and Videos				ImageNet and ModelNet40	
	IN – UCF	IN – HMDB	IN – K400	IN – SSv2	IN – Depth	IN – Shaded
Deit-T	72.0 – 70.0	72.3 – 36.2	72.2 – 44.6	72.2 – 11.2	72.2 – 86.0	72.1 – 81.0
Deit-S	79.8 – 77.2	79.8 – 44.6	79.9 – 53.0	79.9 – 15.3	78.8 – 86.6	79.8 – 86.2
Deit-B	81.9 – 81.4	81.7 – 47.7	81.9 – 57.0	81.8 – 17.5	81.8 – 90.1	81.4 – 88.2
DINO	NA – 79.5	NA – 45.1	NA – 57.4	NA – 17.4	NA – **90.1**	NA– **89.8**
CLIP	NA – **86.0**	NA – **54.6**	NA – **67.3**	NA – **19.9**	NA – 89.5	NA – 88.9

Table 5: ***Spatial along with Temporal Solutions within Image Models:*** Our approach successfully incorporates temporal information into pre-trained and frozen image models and increases their generalization (top-1 (%) at resolution 224) to high-dimensional datasets. The original image solution remains preserved in our approach. Ours Deit-B retains 81.9% top-1 accuracy on ImageNet validation set while exhibiting 81.4% on UCF.

transfer better than CLIP or supervised Deit-B, **c)** Divided space-time attention is more robust than 3D convolution, and **d)** MVCNN trained on shaded rendered views is more robust than depth.

4.1.1 Ensemble Adversarial Transfer

Adversarial attacks optimized from an ensemble of models (Dong et al., 2018; Xie et al., 2019) or self-ensemble (Naseer et al., 2022) increases transferability. We study three types of image ensembles:

$-$*Ensemble of Different Networks:* We transfer attack from three image models of the Deit family (Touvron et al., 2020) including Deit-T, Deit-S and Deit-B. These models differ in architecture.

$-$*Ensemble of Different Training Frameworks:* We transfer attack from three image models including Deit-B, DINO and CLIP. These models share similar architecture but differ in their training.

$-$*Ensemble of Different Spatial Resolutions:* We transfer attack from three image models with the same architecture (Deit-B) but prompt adapted to different spatial resolutions via our approach.

Ensemble of different training frameworks performs favorably to boost attack transferability (Fig. 4). An attacker can adopt our approach at different resolutions to enhance transferability (Table 4). We provide generalization of Deit-B at varying spatial scales for video datasets in Appendix A.

4.2 Adversarial Transfer from Image-to-Image Models

Image datasets are static but we mimic the dynamic behaviour by learning our proposed transformation at different spatial scales (Fig. 2). Our approach exhibit significant gains in adversarial transferability (Table 3). Refer to Appendix B for latent space analysis of class tokens learned at varying scales.

5 Conclusion

In this work, we study the adversarial transferability between models trained for different data modalities (*e.g.*, images to videos). We propose a novel approach to introduce dynamic cues within pre-trained (supervised or self-supervised) image models by learning a simple transformation on videos. Our transformation enables temporal gradients from image models and boost transferability through temporal prompts. We show how our approach can be extended to multi-view information from 3D objects and varying image resolutions. Our work brings attention to the image models as universal surrogates to optimize and transfer adversarial attacks to black-box models.

Reproducibility Statement: Training image models: We adapt pre-trained image models Deit, DINO and CLIP, open sourced by the corresponding authors. We freeze the weights of these models and adapt them for video datasets by introducing our modifications (transformation with temporal prompts). We incorporate the adapted models into the open sourced TimesFormer github repo https://github.com/facebookresearch/TimeSformer and train them with default settings. Training video models: We use the TimesFormer github repo with default settings to train ResNet3D on UCF, HMDB, K-400, and SSv2. Training MVCNN: We use open source code https://github.com/jongchyisu/mvcnn_pytorch to train multi-view models on rendered views (depth, shaded) of ModelNet40. Attacks: We use adversarial attacks with default parameters as described in baseline (Naseer et al., 2022). Datasets: We use the same 5k image samples from ImageNet validation set, open sourced by Naseer et al. (2022), while randomly selected 1.5k samples from the validation sets of explored video datasets. Furthermore, we will release indices of these samples along with all the pre-trained models to reproduce the results.

Ethics Statement: Our work highlights the use of freely available pre-trained image models to generate adversarial attacks. This can be used to create attacks on real-world deep learning systems in the short run. Our work also provides insights on how such attack can emerge from different resources. Therefore, our work provides an opportunity to develop more robust models to defend against such attacks. Further, the image and video datasets used in this work also pose privacy risks which is an important topic we hope to explore in future.

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Appendix

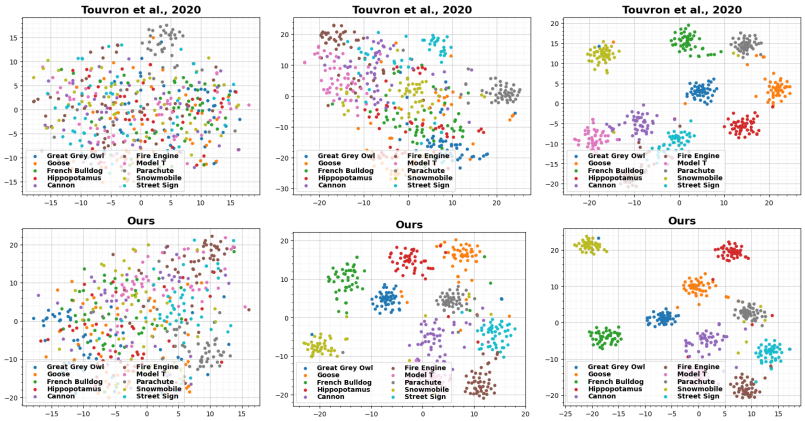
The generalization of image model (Deit-B) at varying spatial scales on video modalities is presented in appendix A. In appendix B, we visualize latent space of class tokens trained at spatial resolution of 224×224 vs our adapted tokens at various spatial resolution scales. The evolution of adversarial patterns across time generated using our approach is provided in appendix C.

A IMAGE MODELS FOR VIDEOS AT VARYING SPATIAL SCALES

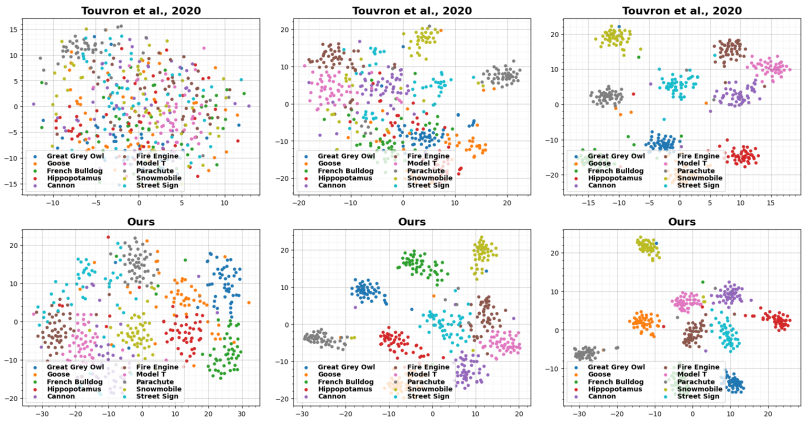
Model	UCF			HMDB		
	224×224	96×96	56×56	224×224	96×96	56×56
DeiT-B	81.4	60.0	32.3	47.7	31.1	15.4

Table 6: ***Adopting image models to videos at varying spatial resolutions (SR):*** We showcase the generalization of DeiT-B model adopted for UCF and HMDB at multiple spatial resolutions.

B VISUALIZING LATENT EMBEDDINGS



The class tokens of DeiT-S models projected from $\mathbb{R}^{384}$ to $\mathbb{R}^{2}$.



The class tokens of DeiT-B models projected from $\mathbb{R}^{768}$ to $\mathbb{R}^{2}$.

Figure 5: We adopted pre-trained Deit models (Touvron et al., 2020) at varying spatial resolutions using our approach; 56×56, 96×96, 120×120 ***(from left to right)***. We showcase inter-class separation and intraclass variation via t-SNE (Van der Maaten & Hinton, 2008) on 10 classes from ImageNet validation set. Our adopted image model have lower intraclass variations and better interclass separation than the original models. We used sklearn (Pedregosa et al., 2011) with perplexity set to 30 for all the experiments. *(best viewed in zoom).*

C VISUAL DEMOS

Figures 6, 7, and 8 shows adversarial pattern from our adapted image models, Deit-B, DINO, and CLIP, for different video samples.

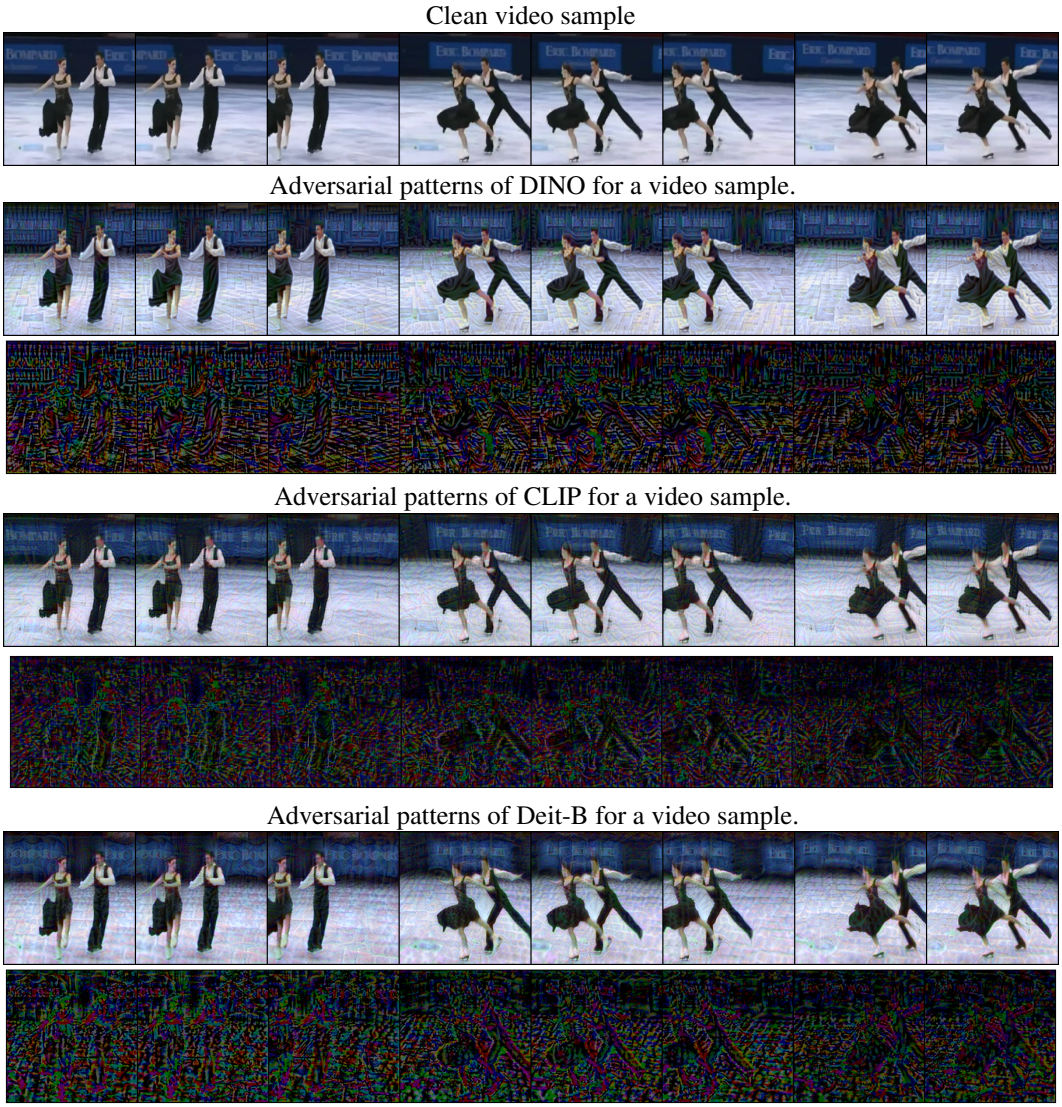


Figure 6: ***Visualizing the behavior of Adversarial Patterns across Time:*** We generate adversarial signals from DINO, CLIP, and DEIT-B models with temporal prompts using DIM attack (Xie et al., 2019). Observe the change in gradients across different frames (*best viewed in zoom*).

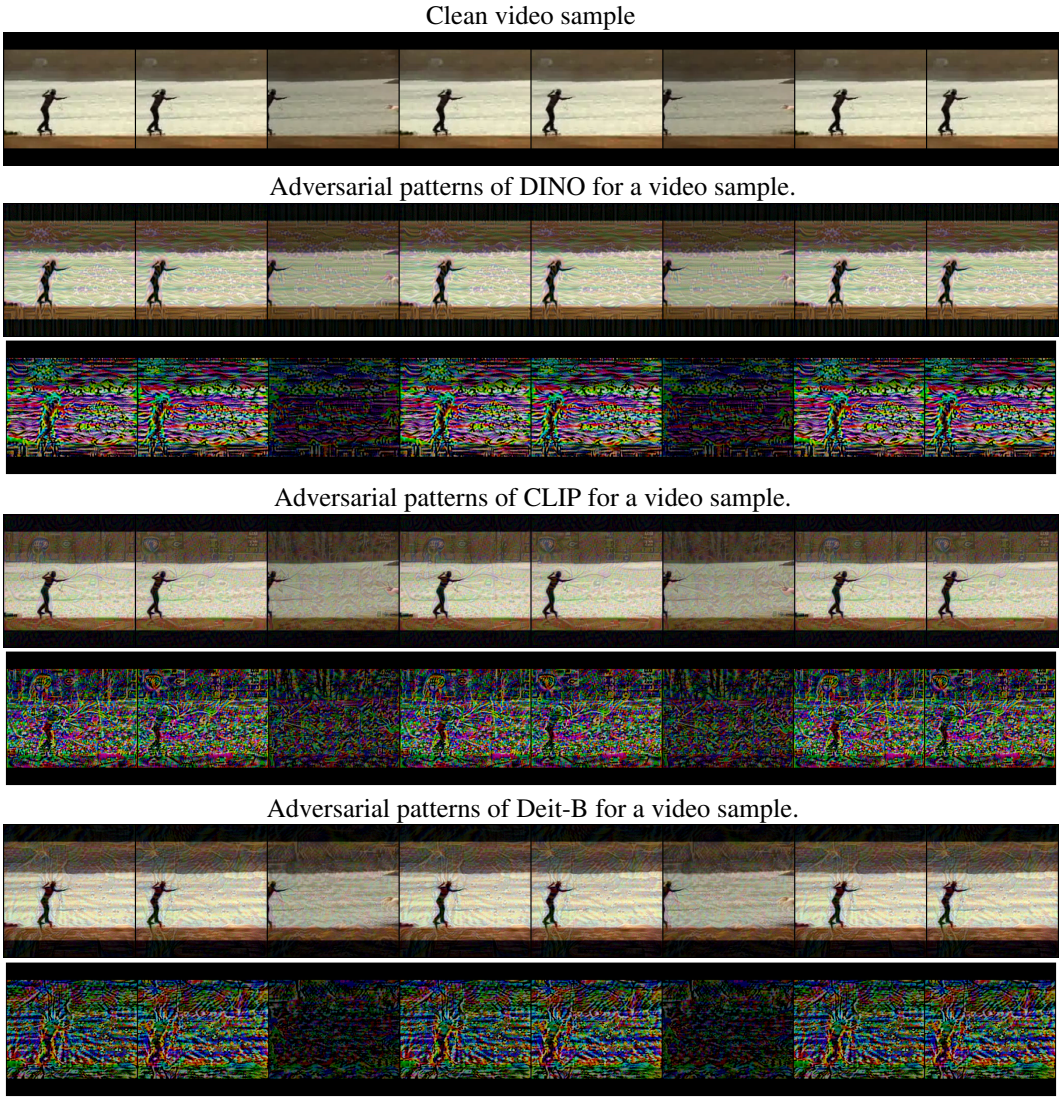


Figure 7: ***Visualizing the behavior of Adversarial Patterns across Time:*** We generate adversarial signals from DINO, CLIP, and Deit-B models with temporal prompts using DIM attack (Xie et al., 2019). Observe the change in gradients across different frames (*best viewed in zoom*).

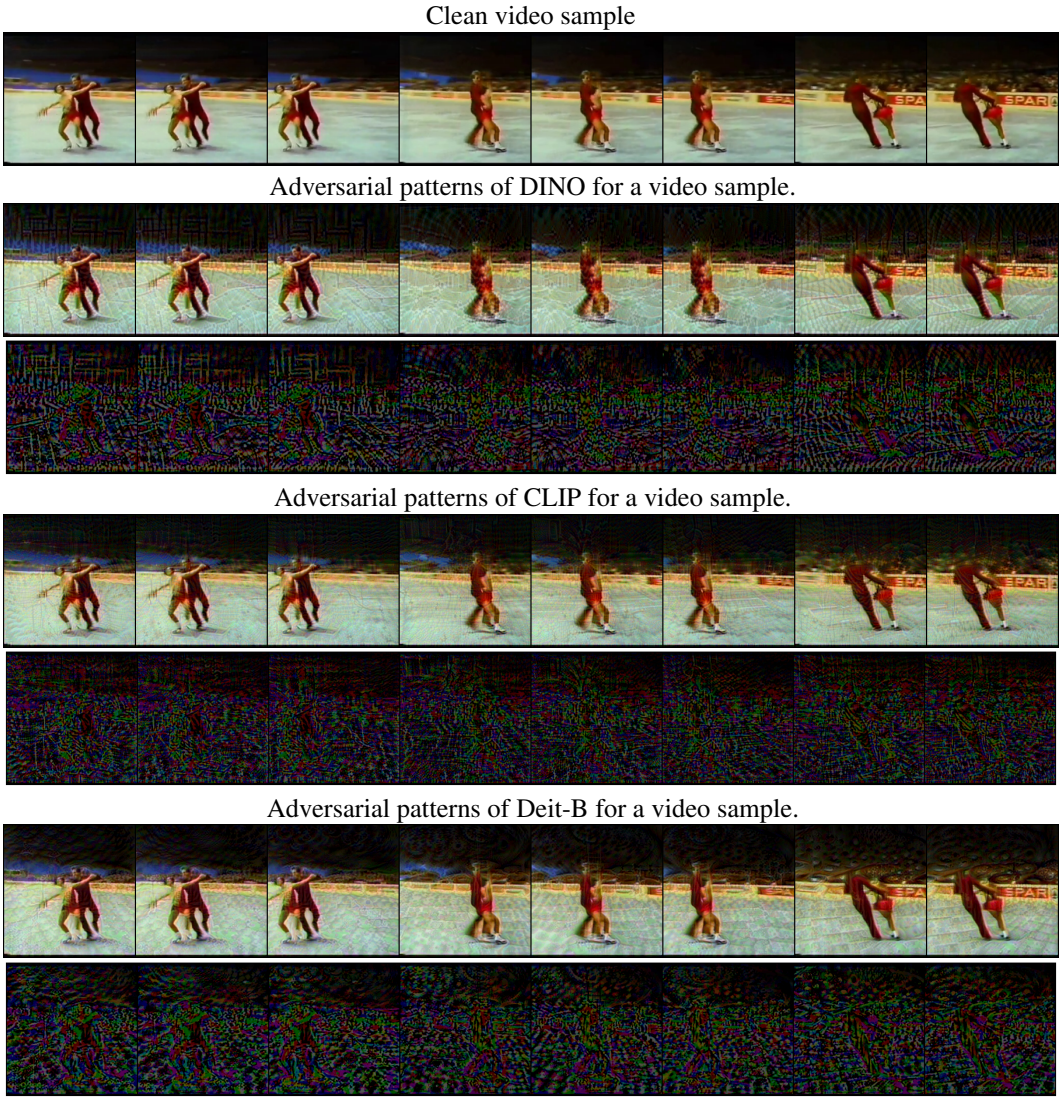


Figure 8: ***Visualizing the behavior of Adversarial Patterns across Time:*** We generate adversarial signals from DINO, CLIP, and Deit-B models with temporal prompts using DIM attack (Xie et al., 2019). Observe the change in gradients across different frames (*best viewed in zoom*).

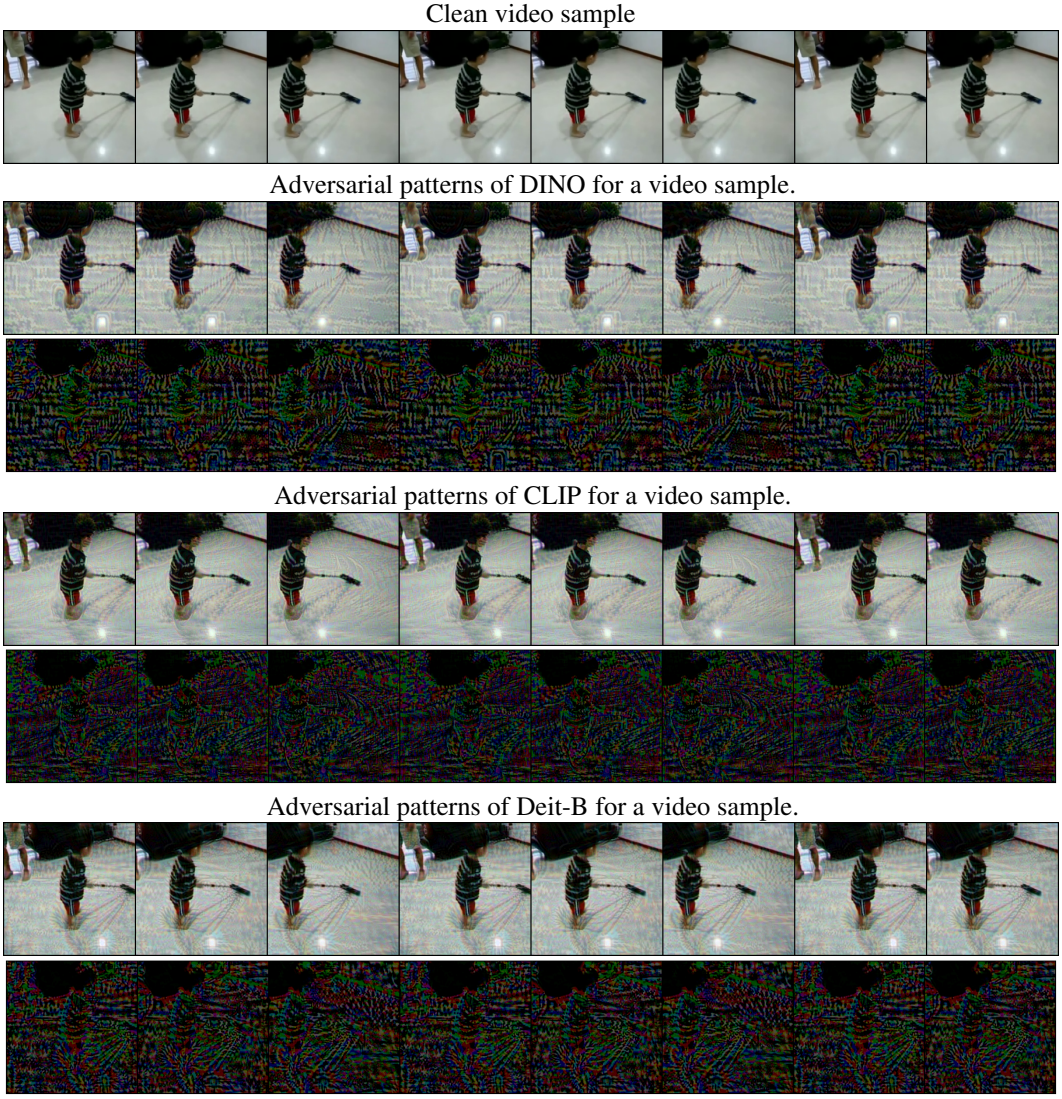


Figure 9: ***Visualizing the behavior of Adversarial Patterns across Time:*** We generate adversarial signals from DINO, CLIP, and Deit-B models with temporal prompts using DIM attack (Xie et al., 2019). Observe the change in gradients across different frames (*best viewed in zoom*).