Perceptron Synthesis Network: Rethinking the Action Scale Variances in Videos

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Abstract

Video action recognition has been partially addressed by the CNNs stacking of fixed-size 3D kernels. However, these methods may under-perform for only capturing rigid spatial-temporal patterns in single-scale spaces, while neglecting the scale variances across different action primitives. To overcome this limitation, we propose to learn the optimal-scale kernels from the data. More specifically, an action perceptron synthesizer is proposed to generate the kernels from a bag of fixed-size kernels that are interacted by dense routing paths. To guarantee the interaction richness and the information capacity of the paths, we design the novel optimized feature fusion layer. This layer establishes a principled universal paradigm that suffices to cover most of current feature fusion techniques (e.g., channel shuffling and channel dropout) for the first time. By inserting the synthesizer, our method can easily adapt the traditional 2D CNNs to the video understanding tasks such as action recognition with marginal additional computation cost. The proposed method is thoroughly evaluated over several challenging datasets (i.e., Somethingto-Something, Kinetics and Diving48) that highly require temporal reasoning or appearance discriminating, achieving new state-of-the-art results. Particularly, our low-resolution model outperforms the recent strong baseline methods, i.e., TSM and GST, with less than 30% of their computation cost.

Introduction

Video action recognition has draw much attentions in computer vision community for its tremendous applications (Tian et al. 2019). Inspired by the breakthrough brought by CNNs on still image recognition task, recent video recognition methods also leverage the 2D CNNs expanded with temporal modeling ability, particularly the 3D CNNs, for spatial-temporal modeling.

3D convolutions are the main operation in the 3D CNNs, which learn spatial-temporal filters to capture visual cues and dynamics of the objects simultaneously. To constrain the parameter number and the computation cost of the whole architecture, most 3D CNNs tend to utilize the filters of typical size $3 \times 3 \times 3$, resulting in a relatively small receptive field. Stacking the small filters and downsampling the features after each stage can enlarge the receptive field to cover the whole input clip. However, there are two issues that limit the performance of down stream tasks. (a) The scale of receptive field w.r.t. each layer is fixed, thus the actions of big objects can only be detected in the deeper layers, resulting in the loss of fine-grained details. (b) The spatial-temporal aspect ratio of receptive field is also fixed, which relies on the hand-crafted tuning for datasets of different complexities.

Fig. 1: (a) Examples from the Something-Something dataset (Goyal et al. 2017). The motion degree (i.e., the green arrow line) and the scale of moving object (i.e., the area of green square box) of different samples are drastically distinct from each other. (b) Example video of “forward and PIKE” from the Diving48 (Li, Li, and Vasconcelos 2018). The action can only be recognized by first discriminating the short-term action primitives and then reasoning the long-term dependence order. Therefore, a powerful method that suffices to handle diverse action variances (in both of spatial and temporal spaces) is critical.
fixed type of kernel with a rigid spatial-temporal receptive field can not handle complex scale variances and thus results in performance degradation. For image recognition, one of the most popular architecture for multi-scale modeling is the Inception networks (Szegedy et al. 2016). However, simply extending this architecture to its 3D version maybe suboptimal because the extended spatial-temporal cube-shaped kernels, e.g., $3 \times 3 \times 3$ and $5 \times 5 \times 5$, are not able to reach the best performance, as shown in the ablation studies.

So, how to decide the optimal-size kernels? Our answer is to learn it from the data. Instead of simply utilizing the NAS (neural architecture search) (Zoph and Le 2016) as in (Piergiovanni, Angelova, and Ryoo 2019), which involves training hundreds of models with huge computation cost, we seek for a soft fusion of the candidate fixed-size kernels with only one-time training. More specifically, we propose an action perceptron synthesizer to continuously generate rich-scale filters from the candidates under the optimization goal: towards the best accuracy for action classification. When the process finished, we freeze the synthesizer and utilize the produced filter group as the optimal. To fully exploit the inter-relations between the fixed-size filters and retain the network capacity to the utmost extent, we propose a novel optimized feature fusion layer as a component of the synthesizer, which provides the dense learnable routing paths among the filters. This layer covers most feature fusion techniques as special cases of it, e.g., channel shuffling (Zhang et al. 2018) and channel dropout. In the experiment part, we demonstrate that the proposed layer achieves conspicuous performance improvement while only introducing marginal learnable parameters and computation cost compared with other conventional feature fusion methods.

Unlike the previous works utilizing single-scale kernels, the synthesizer allows us to deeply exploit the adaptive interactions within the multi-scale spatial and temporal information in each layer when trained on different datasets. By analyzing the statistical distribution of the produced kernels, we demonstrate a series of interpretable insights in the experiment part, which are useful for the hand-crafted designing of future video networks.

We summarize our contributions as follows:

- To cope with the essential spatial-temporal scale variances in the videos, we propose a novel action perceptron synthesizer to generate the optimal-size kernels in each layer instead of simply leveraging the ordinal single-scale kernels of fixed-size.
- We propose an optimized feature fusion layer as a component of the synthesizer to facilitate the inter-connections between the features from different branches, which outperforms other feature fusion methods conspicuously with negligible parameters and costs.
- We perform an extensive ablation analysis of the proposed method and also show some network designing insights from the searching process of the optimal kernel.
- We achieve state-of-the-art on several large scale video datasets with comparable parameters and FLOPs compared to existing approaches.

## Related Works

### Deep Video Recognition

Simonyan et al. (Simonyan and Zisserman 2014a) first proposed the Two-stream framework. Feichtenhofer et al. (Feichtenhofer, Pinz, and Zisserman 2016) then improved it. Later, TSN (Wang et al. 2018a) proposes a new sparse frame sampling strategy. 3D networks, e.g., C3D network (Tran et al. 2015), 1D (Carreira and Zisserman 2017), 3D-ResNet (Hara, Kataoka, and Satoh 2017), i3D (Tran et al. 2020), R(2+1)D CNNs (Tran et al. 2018)(Qu, Yao, and Mei 2017) and Slowfast networks (Feichtenhofer et al. 2019) have recently been an important research line.

### Multi-scale CNN Architectures

CNNs are naturally equipped with multi-scale feature representation ability due to the hierarchical stacking of convolution kernels, e.g., VGGNet (Simonyan and Zisserman 2014b) and ResNet (He et al. 2016). Modern CNN architectures design the multi-scale branches explicitly. The GoogLeNet (Szegedy et al. 2015) utilizes diverse filters with different kernel sizes in parallel to encode the multi-scale feature in each branch. Latter, the Inception Nets (Szegedy et al. 2016) propose to utilize more small filters in each branch of the parallel branches in the GoogLeNet (Szegedy et al. 2015) to further expand the receptive field.

### Efficient Neural Network Designing

Grouped convolution is first introduced in AlexNet (Krizhevsky, Sutskever, and Hinton 2012) and then widely used in later networks, e.g., ResNet (He et al. 2016), for efficient computing. Depthwise convolution is the special case of grouped convolutions, where the feature channel of each group is single. Recent compact models running on mobile platforms such as MobileNetV2 (Sandler et al. 2018) and ShuffleNet (Zhang et al. 2018) leverage the depthwise convolution extensively and achieve effective results. Particularly, ShuffleNet (Zhang et al. 2018) proposes a novel channel shuffling operation for fusing the features produced by different group of convolution filters.

### Approach

In this section, we first propose that the optimal-size spatial-temporal kernel for video modeling can be decomposed into multi-scale spatial and temporal kernels of fixed-size fused by a learnable weight matrix. We further demonstrate that the weight matrix shall obey some explicit constraints and propose an optimized feature fusion layer. Finally, we instantiate our method as an action perceptron synthesizer block and develop a new video modeling network upon the block with an efficient architecture and high performance.

### Optimal Spatial-temporal Kernel Approximation

We first postulate there exists an ideal video CNN, where each layer transforms a 4-dimensional input tensor $U$ of size $C \times T \times W \times H$ into an output tensor $V$ of the same size,
\( V = U \ast \tilde{F}, \) where \( \tilde{F} \) is the optimal convolution kernel with the receptive field of size \( \tilde{T} \times \tilde{W} \times \tilde{H} \). The optimization goal of our method is to approximate \( \tilde{F} \) precisely under the assumption that the upper bound of its receptive field is \( L \times L \times L \).

We propose to synthesize the unknown \( \tilde{F} \) by approximating the produced \( V \) as:

\[
\tilde{V} = \sum_{i=1}^{G} W'(i) \odot \left( \sum_{j=1}^{G} W(j) \odot U \ast F_s^{(2j-1) \times (2j-1) \times 1} \right) \ast F_t^{1 \times 1 \times 2(2i-1)},
\]

where \( G \) denotes the number of branches of different kernel, \( \odot \) denotes the channel-wise multiplication. Each element of \( W' \) and \( W \) is a \( C \)-length vector, indicating the channel-wise importance of the tensor produced by the kernels. We show the derivation process in the supplementary material. Although the representation seems to share some similarities with the R(2+1)D CNNs (Tran et al. 2018), the focus of our method is to produce filters of diverse scales and shapes instead of only saving the computation cost.

The physical meaning behind the Eq. 1 is that the optimal-size spatial-temporal kernel \( \tilde{F} \) can be mimicked by a bag of multi-scale spatial kernels \( F_s = \{ F_s^{1 \times 1 \times 1}, ..., F_s^{L \times L \times 1} \} \) followed by another bag of multi-scale temporal kernels \( F_t = \{ F_t^{1 \times 1 \times 1}, ..., F_t^{1 \times 1 \times K} \} \). The two bags are interacted by \( W \) (\( W' \) is only related to the temporal kernels).

In the next section, we discuss the constraints of \( W \) under the group convolution setting, i.e., (1) \( U = U_1 \oplus U_2 \oplus \ldots \oplus U_C \), where \( G \) denotes the group number. (2) Each kernel of \( F_s \) and \( F_t \) only performs on the one group.

Optimized Feature Fusion Layer

Given the feature \( X = X_1 \oplus X_2 \oplus \ldots \oplus X_C \) produced by spatial convolutions in Eq. 1, \( X_j = U_1 \ast F_s^{(2j-1) \times (2j-1) \times 1} \), where \( j \in [1, G] \), now, we assume there exists a block transformation matrix \( T \in \mathbb{R}^{G \times G} \) performing on \( X \) to produce \( Y = Y_1 \oplus Y_2 \oplus \ldots \oplus Y_G \), as shown in Fig. 2. Noting that \( T \) of size \( G \times G \) is reshaped from \( W \) in Eq. 1 of size \( G \) by dividing the each element of it into \( G \) groups. Each element of \( T \) is a \( c \)-element vector, which is consistent with the channel number of \( X_i \) and \( Y_i \), where \( c = \frac{G}{G} \). We formulate the transformation process above as: \( Y = T \times X \), where the multiplication between each element of \( T \) and \( X \) is channel-wise. In the following parts, we omit the domain of \( i,j \in [1, G] \).

We quantify the routing paths between the spatial and temporal kernels of different size by: \( ir - interactions = \sum_{i=1}^{G} \sum_{j=1}^{G} \sum_{k=1}^{G} \hat{N}_{X_i \rightarrow Y_j}, i \neq j \), where \( \hat{N}_{X_i \rightarrow Y_j} \) denotes the information flowed from \( X_i \) to \( Y_j \), which is measured by the number of feature channels. \( ir - interactions \) indicates the number of the synthesized irregular-shaped spatial-temporal kernels, compared to the regular-shaped kernels of size \( 3 \times 3 \times 3 \) or \( 5 \times 5 \times 5 \). In the experiment part, we show that this metric has strong impact on the performance.

![Figure 2: Schematic representation of Eq. 1 under the group convolution setting. The core of the optimized feature fusion layer is a constrained transformation matrix \( T \), which is reshaped from the \( W \) in Eq. 1. \( \oplus \) denotes the channel concatenation operation.](image)

**Optimization goal:** (1) **Spatial-temporal interaction richness.** We propose the interaction loss formulated as:

\[
\mathcal{L}_{interaction} = -\frac{1}{G^2} \sum_{i=1}^{G} \sum_{j=1}^{G} \text{sigmoid}(||T_{ij}||_1),
\]

where \( || \cdot ||_1 \) denotes the \( \ell_1 \) norm. This loss facilitates higher inter-group interaction richness of \( X \) while regularizing the weights not exploding. By this way, the temporal convolutions after the fusion layer can receive very rich-scale spatial features. In practice, we find the \( ir - interactions \) tends to be \( G^2 \cdot c \) when utilizing this loss.

(2) **High network capacity.** We propose the network capacity loss formulated as:

\[
\mathcal{L}_{capacity} = \frac{1}{G^2} \sum_{i=1}^{G} \sum_{j=1}^{G} \frac{\text{avg}(Y_i) \cdot \text{avg}(Y_j)}{||\text{avg}(Y_i)||_2 \cdot ||\text{avg}(Y_j)||_2},
\]

where \( \text{avg} \) denotes the spatial-temporal average pooling operation, \( \cdot \) and \( || \cdot ||_2 \) denotes Dot product and \( \ell_2 \) norm respectively. This loss facilitates the lower inter-group similarity within \( Y \) and thus leads to the wider network of higher capacity in essence.

**vs. Other feature fusion techniques.** We assume that each weight vector \( T_{ij} \) in \( T \) is also sub-grouped into \( G \) groups: \( T_{ij} = T_{ij}(1) \oplus \ldots \oplus T_{ij}(G) \). Then, under the framework of the proposed layer, channel shuffling (Zhang et al. 2018) can be represented as:

\[
\{ T_{ij}(k) = 1, k = i, \ T_{ij}(k) = 0, \text{others} \},
\]

where \( k \in [1, G] \), 1 and 0 denote all-one and all-zero vectors of size \( \frac{G}{G} \) separately. Further comparing with other conventional feature fusion techniques as a special cases of our method is in the supplementary material.

**Action Perceptron Synthesizer.** We wrap the approximated optimal spatial-temporal operation in Eq. 1 into an action perceptron synthesizer that can be incorporated into many existing architectures. The
synthesizer is defined as: \( z_i = V_i + U_i \), where \( V_i \) is given in Eq. (1) and “+U_i” denotes a residual connection [He et al., 2016]. The residual connection allows us to insert the proposed synthesizer into any pre-trained model such as ResNet, without breaking its initial behavior (e.g., when \( W \) in Eq. (1) is initialized as zero). An example action perceptron synthesizer is illustrated in Fig. 3. The optimized feature fusion layer can be simply implemented as a fully-connected layer regularized by \( L_{\text{interaction}} \) and \( L_{\text{capacity}} \).

**Video Perceptron Synthesis Networks.** The proposed action perceptron synthesizer is flexible and can be easily integrated with most of the current 2D or 3D CNNs. More specifically, we adopt 2D-ResNet-50 [He et al., 2016] as the backbone networks and insert the proposed synthesizer between the residual blocks. The final prediction is a simple average pooling of the results from each frame. We conduct extensive experiments on the different variants of it.

**End-to-end learning for action recognition.** Finally, we apply the proposed networks to the action recognition task. The total loss is given by \( L = L_{\text{classification}} + \alpha L_{\text{interaction}} + \beta L_{\text{capacity}} \), where \( L_{\text{classification}} \) is the cross-entropy loss, \( \alpha \) and \( \beta \) are the balancing weights.

## Experiments

**Video Datasets**

**Something-Something.** This dataset includes v1 [Goyal et al., 2017] and v2 [Mahdisoltani et al., 2018]. We mainly conduct ablation experiments and justify each component on Something-Something v1 dataset.

**Kinetics.** Kinetics [Carreira and Zisserman, 2017] is a challenging human action recognition dataset. The actions in this dataset mainly rely on the appearance of the objects and the background scenes to be discriminated.

**Diving48.** Diving48 [Li, Li, and Vasconcelos, 2018] is a new dataset with more than 18k video clips for 48 ambiguous diving classes, requiring multi-scale temporal modeling. We report the accuracy on the official train/val split.

## Implementation Detail

We implement our model in Pytorch [Paszke et al., 2019]. We adopt ResNet50 [He et al., 2016] pretrained on ImageNet [Deng et al., 2009] as the backbone. The parameters within the action perceptron synthesizers are randomly initialized. The synthesizers are inserted after the conv5 layers if no specified otherwise. For the temporal dimension of the input clips, we use the sparse sampling method described in TSN [Wang et al., 2016]. For spatial dimension, the short-side of the input frames are resized to 256 and then cropped to 224 x 224. We do random cropping and flipping as data augmentation during the training. We train the network with a batch-size of 64 on 8 NVIDIA GTX-2080Ti GPUs and optimize it using SGD with an initial learning rate of 0.01 for 50 epochs and decay it by a factor of 10 every 10 epochs. The total training epochs are about 80. To train the total loss, we set the balancing weights of the losses as: \( \alpha = 0.01 \) and \( \beta = 0.001 \) by grid searching. The dropout ratio is set to be 0.3 as in [Luo and Yuille, 2019]. During the inference, we sample the middle frame in each segment and do center crop for each frame. We report the results of 1 crop unless specified. Note that many state-of-the-art methods report their final performances with 5 or 10 crops, which enlarge the inference-time computation cost by 5 or 10 times. Moreover, we only use RGB modality as the input to our model.

## Ablation Study

We conduct extensive ablation studies on the Something-Something V1 [Goyal et al., 2017] dataset to demonstrate the effectiveness of every aspects of our method. All the synthesizers in these experiments are of maximum receptive filed \( 5 \times 5 \times 5 \) as shown in Fig. 3 and performed on the 1/4 proportion of input features if no specified otherwise. To facilitate the training process, in these experiments, we adopt a smaller input resolution: the short-side of the input frames are resized to 128 and then the frames are cropped to 112 x 112.
| Methods                  | Backbone    | Maximum RFS | Synthesized kernel shapes | Irregular shape? | Multi-scale? Parameters | Sth v1 Top1 (%) | Top5 (%) |
|-------------------------|-------------|-------------|----------------------------|------------------|-------------------------|----------------|----------|
| TSN (Wang et al. 2016)  | ResNet50    | -           | -                          | -                | -                       | 23.87M         | 36.97    |
| TSM (Lin, Gan, and Han 2019) | ResNet50    | 1 × 3       | 1                          | ✓                | -                       | 23.87M         | 71.01    |
| GST (Luo and Yuille 2019) | ResNet50    | 3 × 3       | -                          | -                | -                       | 21.04M         | 71.42    |
| GST (Luo and Yuille 2019) | ResNet101   | 3 × 3       | 1                          | ✓                | -                       | 37.52M         | 69.76    |
| RF-S                    | ResNet50    | 3 × 3       | 1                          | -                | -                       | 27.37M         | 73.14    |
| RF-L-Inception          | ResNet50    | 5 × 5       | 1                          | -                | -                       | 27.55M         | 74.98    |
| RF-L-Inception-T        | ResNet50    | 1 × 4       | ✓                          | ✓                | ✓                       | 27.28M         | 72.87    |
| Ours                    | ResNet50    | 5 × 5       | 16                         | ✓                | ✓                       | 27.55M         | 74.12    |
| Ours-1/16               | ResNet50    | 5 × 5       | 16                         | ✓                | ✓                       | 24.05M         | 72.65    |

Table 1: Results of inserting different spatial-temporal blocks to 2D ResNet-50. The evolution of the performance improvement can be explained by diverse shape synthesized kernels, especially the introduction of irregular shape kernels, and multi-scale design. † indicates that the results are reproduced under the same input size with us.

| Methods | ir – interactions | Dropout rate | Parameters | Sth v1 |
|---------|-------------------|--------------|------------|--------|
| Channel grouping | U | 0 | 0M | 43.84 | 72.29 |
| Channel dropout   | 1856 | 0.75 | 0M | 44.84 | 73.05 |
| Channel shuffling | 1856 | > 0 | 0.086 M | 45.01 | 73.53 |
| Ours | < 1856 | > 0 | 0.086 M | 45.44 | 74.12 |
| Ours+Lc | ~ 1856 | > 0 | 0.086 M | 46.12 | 74.92 |
| Ours+Lc | < 1856 | 0 | 0.086 M | 45.88 | 74.22 |
| Ours+Lc | ~ 1856 | 0 | 0.086 M | 46.41 | 75.01 |

Table 2: Comparison of different feature fusion methods. Larger ir – interactions and lower dropout rate bring more performance gain. Lc and Lc denotes Linteraction and Lcapacity respectively. Architecture details are in supplementary material.

To emphasize the importance of two important philosophies in our method: (a) multi-scale modeling and (b) optimal-size kernels synthesizing especially the irregular-shaped kernels, we compare against the following baselines: (1) The vanilla TSN (Wang et al. 2016), (2) RF-S model shown in Fig. 4(a), (3) RF-L model shown in Fig. 4(b), (4) RF-L-Inception model shown in Fig. 4(c), (5) RF-L-Inception-T model shown in Fig. 4(d). The architecture details are in the supplementary material.

The superiority of action perceiver synthesiser As shown in Tab. 1, our method mine the spatial-temporal reasoning information much better. Compared with the RF-L-Inception model, our method improves the performance significantly with almost no extra computation cost, thanks to the kernels of much more diverse shapes (16 vs. 4), especially the irregular shape, introduced by the synthesizers.

Also, multi-scale modeling widely adopted in the modern CNNs only contributes marginal performance gain: 0.17% (RF-L vs. RF-L-Inception) whereas rich kernel shape brings conspicuous improvement: 1.60% (RF-L-Inception vs. our method) in terms of Top1 accuracy. Interestingly, only enlarging the maximum receptive field in a naive way, i.e., from RF-S model to RF-L model, the performances are degraded slightly. We conjecture that the degradation is caused by the smaller enhanced spatial-temporal feature proportion of RF-L model (1/6 vs. 1/8), which will be discussed in supplementary material. The large performance improvement of RF-L-Inception-T upon TSM also proves the merits of learnable multi-scale temporal modeling. To compare with TSN and TSM rigorously, we also set the feature proportion of our method as 1/16, resulting the comparable parameter number as them. Our method outperforms TSM by 1.89% in terms of Top1 accuracy although TSM performs temporal modeling on more feature maps (1/8 of the input feature maps). Compared to GST, our method enhances the spatial features with the spatial-temporal information by adding instead of replacing. All of our baselines even including the RF-S model outperform GST, proving the superiority of retaining the complete spatial appearance prior learned on image tasks. GST has less parameters even than the simplest TSN because it sacrifices the channel number of spatial features, showing over-fitting when leveraging the ResNet101 as the backbone network.

The superiority of optimized feature fusion layer As shown in Tab. 2, when utilizing plain channel grouping operation between the spatial and the temporal filters, our method degenerates to the RF-L-Inception baseline and shows the most inferior performance for not synthesizing rich-scale spatial-temporal kernels. The synthesizing process relies on the irregular routing paths quantified by ir – interactions, which is 0 in this situation. The performance improves consistently with larger ir – interactions and lower dropout rate. Notably, the dropout based fusion method (detailed in supplementary material) still outperforms the baseline largely while discarding a large proportion of spatial features, implying the synthesized irregular-shaped kernels measured by ir – interactions have more direct impact on the final performance. Channel shuffling demonstrates the best performance under the premise of not introducing extra parameters. However, its performance
is worse than our method even without any regularization (45.01% vs. 45.44%) because it is un-learnable and can not adjust the weights of the routing path dynamically for synthesizing the optimal kernels in a data-driven way. With the both two proposed regularizations (L\textsubscript{interaction} and L\textsubscript{capacity}) activated, our method improves the performance by near another 1%.

**Studies on network details** In the supplementary material, we show the ablation studies on Where to insert the block? and What proportion of features need to be enhanced with space-temporal features? Then, we demonstrate the studies on the detailed design of our block in Tab. 5 the pooling operation improves the performance significantly (1.25% Top1 accuracy) while our method is not sensitive to the specific implementation of the operation. The extra non-linearity introduced by the intermediate ReLU operations between spatial- and temporal- filters also benefits the performance obviously, which is consistent with the conclusion from previous work (Tran et al., 2018). The dilated convolution outperforms the ordinary convolution by 1.24% in terms of Top5 accuracy even with less parameters, showing better generalization ability. Finally, we also try to decompose the spatial convolutions. As shown in the last block of Tab. 5 compared to the (2+1) D setting, the (1+1+1) D truly reduces negligible number of parameters but also degrades the performance.

**Comparison with State-of-the-Art**

**Something-V1** The recognition performance obtained by our method is compared with state-of-the-art approaches that just use RGB frames, as shown in Tab. 4. The maximum RFS is 5×5×7 by grid searching. The results w.r.t. the other RFSs is in the supplementary material. We also adopt this hyper-parameter for the other two datasets. The first block of the table shows the approaches that utilize Full-3D CNNs. The second block of the table lists methods leveraging 2D CNN or efficient 3D CNN implementation. From the table, it can be seen that our method results in an absolute gain of +34.1% (19.5% vs. 53.6%) over the TSN baseline. Our method performs better than 3D CNNs or heavier backbones with considerably less number of FLOPs. Under several common testing protocols, our method outperforms the most recent works significantly with comparable computational budget. Moreover, when adopting inputs of lower spatial resolution, i.e., 112×112, our method still achieves competitive result (47.2% top1 accuracy) with the recent methods such as TSM and GST, with much lower computation cost (<30% of them). The analysis on the sensitivity of the methods to the input spatial resolution are in the supplementary material and demonstrates that our method show the lowest sensitivity.

**Kinetics-400** As shown in Tab. 5 our method also captures rich object appearance cues effectively. Our method achieves inferior performance compared to some 3D CNN methods, i.e., 13D and SlowFast networks. However, they both adopt much deeper and heavier 3D-ResNet-101 as the backbone network. They also leverage the inefficient non-local operation to model the long-range temporal dependen-cies. When comparing with the methods based on 2D CNNs, our method outperforms them largely and demonstrates the best trade-off between the action recognition accuracy and the computation cost.

**Diving48** To prove that our method can model long-term complex fine-grained motion cues and is not prone to over-fitting on few training samples, we test out method on Diving48. We input 16 frames to the network and sample only one or two clip from the video during inference. The results are shown in Tab. 6. Our method achieves significant improvement over the most recent state-of-the-arts, i.e., over 1% under the input of 16 frames.

**Visualization**

Figure 5: Visualization of spatial-temporal filter interactions of different layers (i.e., Conv1 ~ 4) over multiple datasets. The deeper color, the denser interaction. The filters are denoted by a triplet-abbreviation, i.e., “domain-type-kernelsize”, as shown in the vertical and horizontal axes of the up-left sub-figure. S and T denotes spatial and temporal domain, C, M and I denotes convolution, max-pooling and identity. For example, S-C-3 denotes the spatial convolution with 3×3 kernel size. All the sub-figures share the same axes caption as the up-left one for brevity. Best viewed by zooming in.

To understand how spatial and temporal information are interacted in the action perceptron synthesizer to form the optimal kernel, we check the weights of the proposed optimized feature fusion layer in the synthesizer after each residual block of the ResNet-50 backbone, as shown in Fig. 5. Specifically, we quantize the importance of different shape interactions as the \(l_1\) norm of the corresponding transformation matrix, i.e., \(T_{ij}\) in Eq. (4). We first find that the over-all distribution learned on Something-Something v1 (first row) is non-sparse, indicating the rich-scale spatial-temporal modeling is necessary. Moreover, the max-pooling operation occupies considerable importance for serving as a hard attention strategy to find the local key contexts, which is consistent with the quantitative comparison in Tab. 5. Also, we find the receptive range of the operation evolves from spatial- to temporal- to spatial-temporal. We further visualize the statistics of the models trained on different datasets. For datasets requiring temporal information such
as Something-Something v1 (first row in Fig. 5) and Diving48 (third row in Fig. 5), we can see the models begin to aggregate the features by $3 \times 1 \times 1$ or $5 \times 1 \times 1$ temporal convolutions in the first stage, which is not learned out from Kinetics-400 in the early stage. Kinetics-400 involves richer spatial-temporal interactions in the second stage (as shown in the second column of the second row in Fig. 5) for its more diverse background scenes and more complicated object interactions happening in the wild. Moreover, for stage 2, 3 and 4, compared to another two datasets, the most interactions of the model trained on Kinetics-400 concentrate on the temporal max-poolings instead of the temporal convolutions, which aligns with the fact that most action primitives in Kinetics are chronologically irrelevant.

We demonstrate more analysis w.r.t. the most improved classes by our method, action distribution in the feature space, action activation map and the temporal evolution of predictions in the supplementary material.

### Conclusion
To tackle the essential spatial-temporal scale variances in videos, we propose to learn the optimal-scale kernels from the data and instantiate our method as the action per-ception synthesizer block. We perform extensive evaluations to study its effectiveness on video action recognition task, achieving state-of-the-art results. We also demonstrate some visualization results for more intuitive understanding of our method.

### Table 4: Comparison to state-of-the-art on Something-V1 validation set.

| Method | Backbone | Pre-train | #Frames | GFLOPs | Top1 (%) | Top5 (%) |
|--------|----------|-----------|---------|--------|----------|----------|
| TSN (Wang et al. 2016) | R(2+1)D (Sudhakaran, Escalera, and Lanz 2018) | BU-Inception | ImageNet | 8 × 1 | 16 × 1 × 1 | 19.5 |
| STM (Jiang et al. 2019) | ResNet-50 | | | | |
| TSM (Lin, Gan, and Han 2019) | ResNet-50 | | | | |
| GST (Luo and Yuille 2019) | ResNet-50 | | | | |
| TEA (Li et al. 2020) | ResNet-50 | | | | |
| TEA (Li et al. 2020) | ResNet-50 | | | | |

Table 5: Comparison to state-of-the-art on Kinetics-400.

| Method | Backbone | Pre-train | #Frames | GFLOPs | Top1 (%) | Top5 (%) |
|--------|----------|-----------|---------|--------|----------|----------|
| TSN (Wang et al. 2016) | R(2+1)D (Tran et al. 2018) | BU-Inception | ImageNet | 25 × 10 × 1 | 53 × 10 × 1 | 69.1 |
| TSM (Lin, Gan, and Han 2019) | ResNet-50 | | | | |
| TSM (Lin, Gan, and Han 2019) | ResNet-50 | | | | |
| GST (Luo and Yuille 2019) | ResNet-50 | | | | |
| TEA (Li et al. 2020) | ResNet-50 | | | | |
| TEA (Li et al. 2020) | ResNet-50 | | | | |

Table 6: Comparison to state-of-the-art on Diving48.
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