TimeSformer: Is Space-Time Attention All You Need for Video Understanding?

```
paper:  https://arxiv.org/abs/2102.05095
accept: ICML2021
author: Facebook AI
code(offical):  https://github.com/facebookresearch/TimeSformer
```

一、前言

Transformers(VIT)在图像识别领域大展拳脚，超越了很多基于Convolution的方法。视频识别领域的Transformers也开始'猪突猛进'，各种改进和魔改也是层出不穷，本篇博客讲解一下FBAI团队的**TimeSformer**，这也是第一篇使用纯Transformer结构在视频识别上的文章。

二、出发点

- **Video vs Image**
  1. Video是具有时序信息的，多个帧来表达行为或者动作，相比于Image直接理解pixel的内容而言，Video需要理解temporal的信息。
- **Transformer vs CNNs**
  1. 相比于Convolution，Transformer没有很强的归纳偏置，可以更好的适合大规模的数据集。
  2. Convolution的kernel被用来设计获取局部特征的，所以不能对超出'感受野'的特征信息进行建模，无法更好的感知全局特征。而Transformer的 `self-attention` 机制不仅可以获取局部特征同时本身就具备全局特征感知能力。
  3. Transformer具备更快的训练和推理的速度, 可以在与CNNS在相同的计算下构建具有更大学习能力的模型。(这个来自于VIT)
  4. 可以把video视作为来自于各个独立帧的patch集合的序列，所以可以直接适用于VIT结构。
- **Transfomrer自身问题**
  1. `self-attention` 的计算复杂程度跟token的数量直接相关，对于video来说，相比于图像会有更多的token(有N帧), 计算量会更大。

三、算法设计

Transformers有这么多的优点，所以既要保留纯粹的Transformer结构，同时要修改 `self-attention` 使其计算量降低并且可以构建Temporal特征。

构建VideoTransformer

我们先梳理一下Video怎么输入到Transformer中: 对于Video来说，输入为$X \in \mathbb{R}^{H \times W \times 3 \times F}$, 表示为F帧采样的尺寸为$H \times W$的RGB图像。Transformer需要patch构建sequence进行输入，所以有$N = HW/P^2$，这里P表示的是patchsize大小，N表示的是每帧有多少个patch。展开后，可以表示为向量$X(p,t) \in \mathbb{R}^{3P^2}, p = 1, ..., N, t = 1, ..., F$。

对输入做Embeeding处理，$z_{(p,t)}^{(0)} = EX(p,t) + e_{(p,t)}^{pos}$, 这里$E \in \mathbb{R}^{D \times 3P^2}$表示为一个可学习的矩阵，$e_{(p,t)}^{pos} \in \mathbb{R}^{D}$表示一个可学习空间位置编码。相比于Image的 `cls-token` ， Video的 `cls-token` 表示为 $z_{(0,0)}^{(0)}$。

Transformer整体包含L层encoding blocks, 每个block的query,key,value表达如下:

$$
\begin{aligned}
q_{(p,t)}^{(l,a)} &= W_Q^{(l,a)} LN(z_{(p,t)}^{(l-1)}) \in \mathbb{R}^{D_h} \\
k_{(p,t)}^{(l,a)} &= W_K^{(l,a)} LN(z_{(p,t)}^{(l-1)}) \in \mathbb{R}^{D_h} \\
v_{(p,t)}^{(l,a)} &= W_V^{(l,a)} LN(z_{(p,t)}^{(l-1)}) \in \mathbb{R}^{D_h}
\end{aligned}
$$

这里，$a = 1, ..., A$表示attention heads数量，D_h表示的是每个head的维度。

相比于Image的self-attention, Video的self-attention需要计算temporal维度，公式表达为:

$$
\begin{aligned}
a_{(p,t)}^{(l,a)} &= Softmax\left(\frac{q_{(p,t)}^{(l,a)\ T}}{\sqrt{D_h}} \cdot \left[k_{(0,0)}^{(l,a)} \left\{ k_{(p',t')}^{(l,a)} \right\}_{\substack{p'=1,...,N \\ t'=1,...,F}} \right] \right) \\
s_{(p,t)}^{(l,a)} &= a_{(p,t),(0,0)}^{(l,a)} v_{(0,0)}^{(l,a)} + \sum_{p'=1}^{N} \sum_{t'=1}^{F} a_{(p,t),(p',t')}^{(l,a)} v_{(p',t')}^{(l,a)}
\end{aligned}
$$

Note: 公式里把 `cls-token` 单独提出来了，这样方便表达空间和时序维度的attention。

合并每个heads的attention后，进行一个线性投影，送入MLP中，同时进行一个残差连接和Image的Transformer没有区别，公式表达如下:

$$
\begin{aligned}
z'^{(l)}_{(p,t)} &= W_O \begin{bmatrix} s_{p,t}^{(l,1)} \\ \vdots \\ s_{p,t}^{(l,A)} \end{bmatrix} + z_{(p,t)}^{(l-1)} \\
z_{(p,t)}^{l} &= MLP(LN(z'^{(l)}_{(p,t)})) + z'^{(l)}_{(p,t)}
\end{aligned}
$$

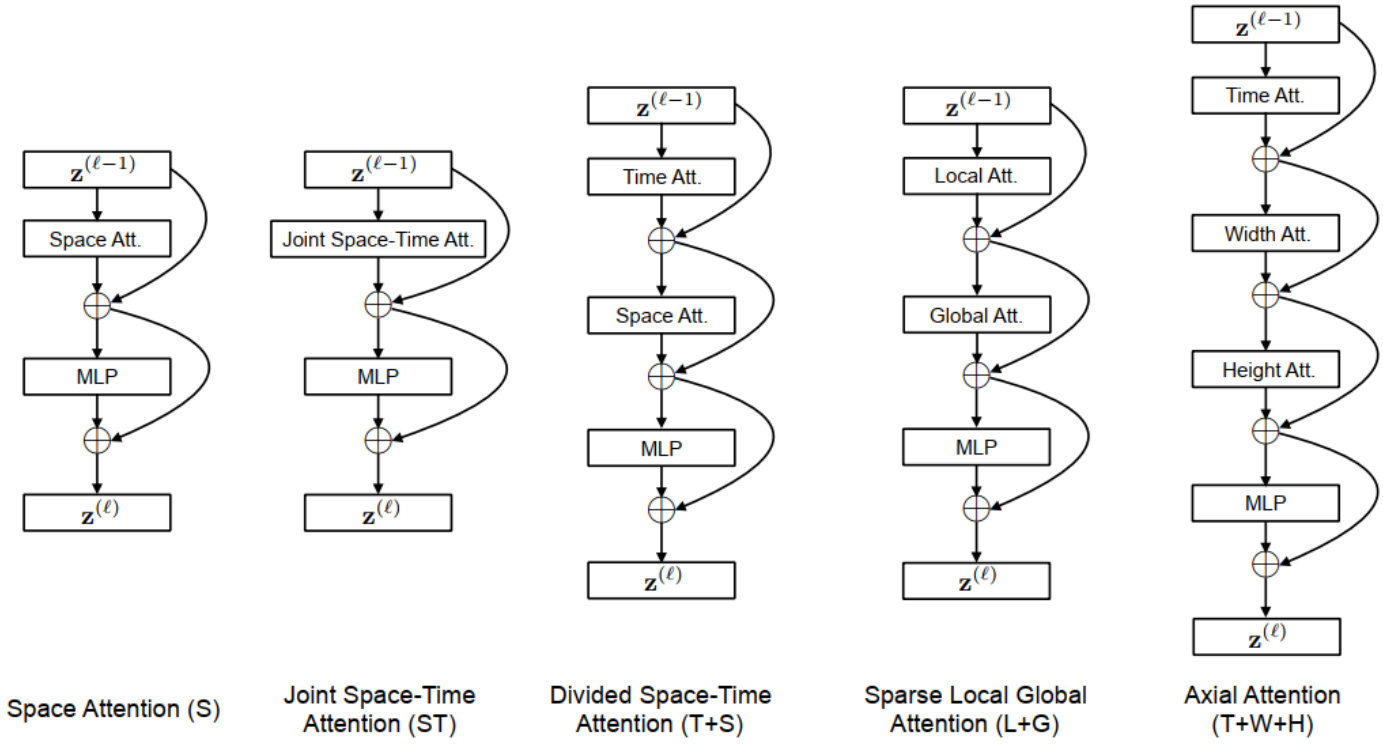
最后就是分类层了，取 `cls-token` 用于最终的分类。

$$
y = MLP(LN(z_{(0,0)}^{l}))
$$

这样，我们就可以得到一个从输入到输出的VideoTransformer的完整表示。知道了怎么输入输出，接下来讨论怎么改进更好的获取temporal特征信息。

Self-Attention范式

为了解决时序的问题，文中提出了几种构建范式，如下图所示:



- **SpaceAttention(S)**
  这种就是标准的Transformer结构了，不计算Temporal的信息，只计算空间信息。公式可以表达为:

$$a_{(p,t)}^{(l,a)} = Softmax\left(\frac{q_{(p,t)}^{(l,a)\ T}}{\sqrt{D_h}} \cdot \left[k_{(0,0)}^{(l,a)} \left\{k_{(p',t)}^{(l,a)}\right\}_{p'=1,\ldots,N}\right]\right)$$

- **Joint Space-Time Attention(ST)**
  这种就是把temporal和空间的token拉伸在一起，计算量会变得很大($O((n+1)^2)$ -> $O((n*t+1)^2)$)。公式表达为:

$$a_{(p,t)}^{(l,a)} = Softmax\left(\frac{q_{(p,t)}^{(l,a)\ T}}{\sqrt{D_h}} \cdot \left[k_{(0,0)}^{(l,a)} \left\{k_{(p',t')}^{(l,a)}\right\}_{\substack{p'=1,\ldots,N \\ t'=1,\ldots,F}}\right]\right)$$

- **Divided Space-Time Attention(T+S)**
  相比于前两种，这个变种的attention计算分成了两步，第一步计算Temporal-self-attention，第二步计算Spatial-self-attention，复杂度则会变为($O((n*t+1)^2)$ -> $O((n+t+2)^2)$),每一次计算都会有 `cls-token` 参与，所以需要+2。公式表达如下:

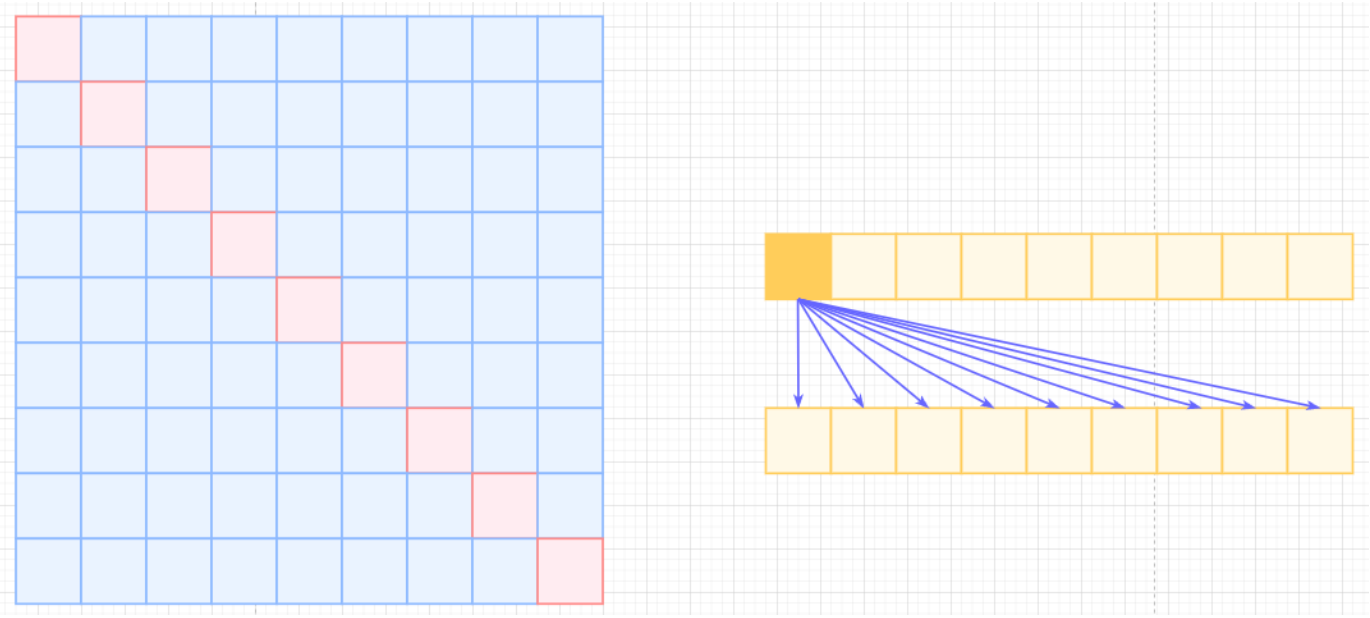
$$a^{(l,a)}_{(p,t)\,spatial} = Softmax\left(\frac{q^{(l,a)\,T}_{(p,t)}}{\sqrt{D_h}} \cdot \left[k^{(l,a)}_{(0,0)} \left\{k^{(l,a)}_{(p',t)}\right\}_{p'=1,\dots,N}\right]\right)$$

$$a^{(l,a)}_{(p,t)\,temporal} = Softmax\left(\frac{q^{(l,a)\,T}_{(p,t)}}{\sqrt{D_h}} \cdot \left[k^{(l,a)}_{(0,0)} \left\{k^{(l,a)}_{(p,t')}\right\}_{t'=1,\dots,F}\right]\right)$$

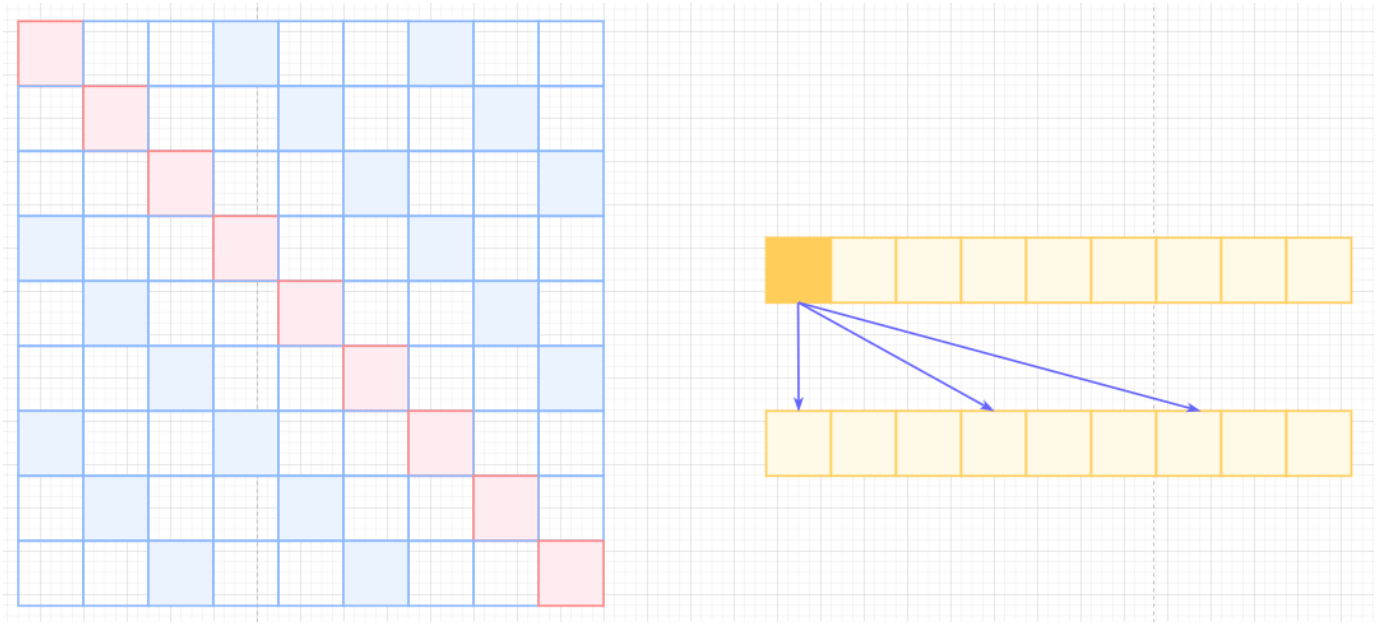
两步独立计算且意义不同，所以Q,K,V需要来自不同的weights，不能共享权重。简单的定义为:

$$W^{(l,a)}_{Q^{space}}, W^{(l,a)}_{K^{space}}, W^{(l,a)}_{V^{space}}$$
$$W^{(l,a)}_{Q^{time}}, W^{(l,a)}_{K^{time}}, W^{(l,a)}_{V^{time}}$$

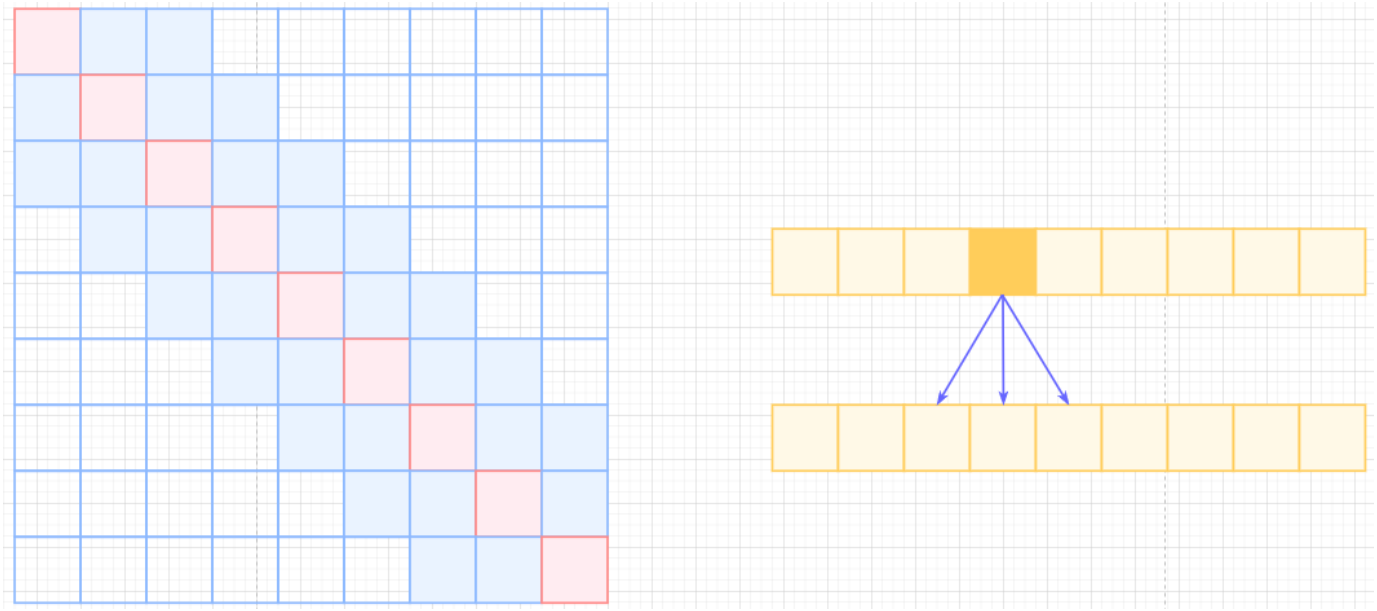
- **Sparse Local Global Attention (L+G)**
  这个attention文章只做了简单的描述，没有给出相关代码实现，这里参考了Generating Long Sequences with Sparse Transformers文章，做一个简单的解释。
  先引入几个概念和图示
  Self-Attention, 左边是self-attention矩阵，右边是对应的相乘关系，复杂度为$O(n^2)$。



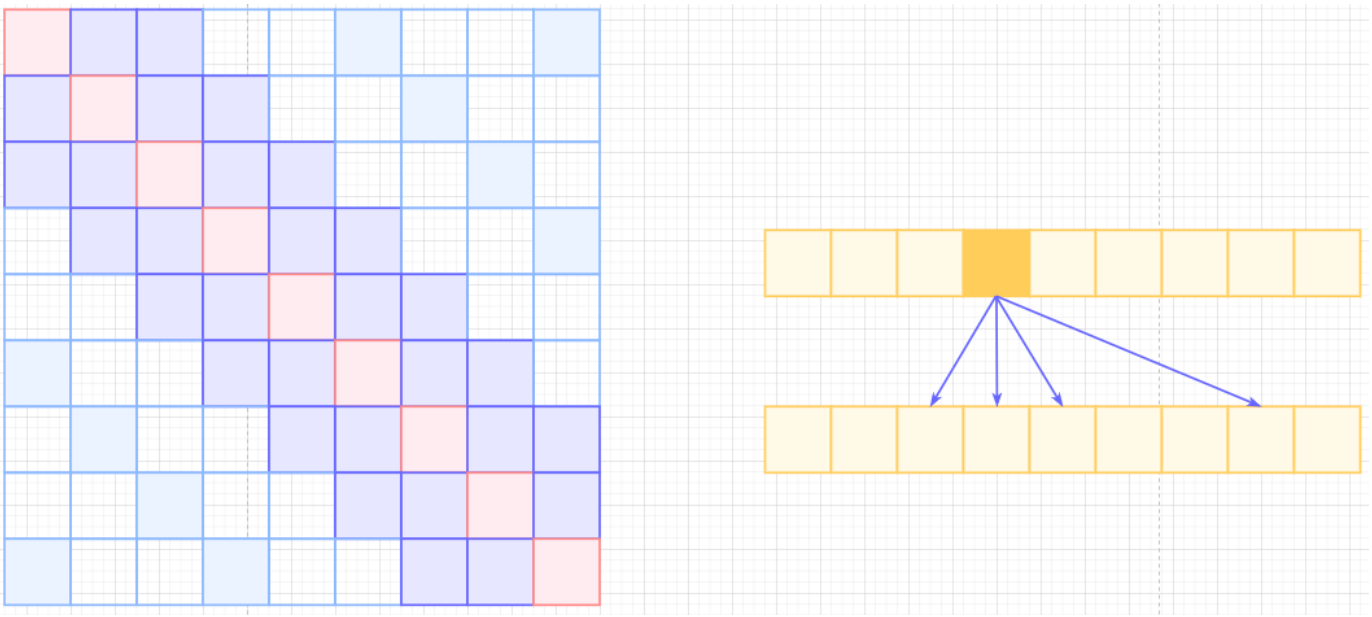
Atrous Self-Attention，为了减少计算复杂度，引用空洞概念，类似于空洞卷积，只计算与之相关的k个元素计算，这样就会存在距离不满足k的倍数的注意力为0，相当于加了一个k的stride的滑窗，如下图中的白色位置。这样复杂度可以从$O(n^2)$降低到$O(n^2/k)$。



Local Self-Attention, 标准self-attention是用来计算 `Non-Local` 的，那也可以引入局部关联来计算local的，很简单，约束每个元素与自己k个邻域元素有关即可，如下图，复杂度为$O((2k+1)*n)$, 也就是$O(kn)$, 计算复杂度直接从平方降低到了线性，也损失了标准self-attention的长距离相关性。

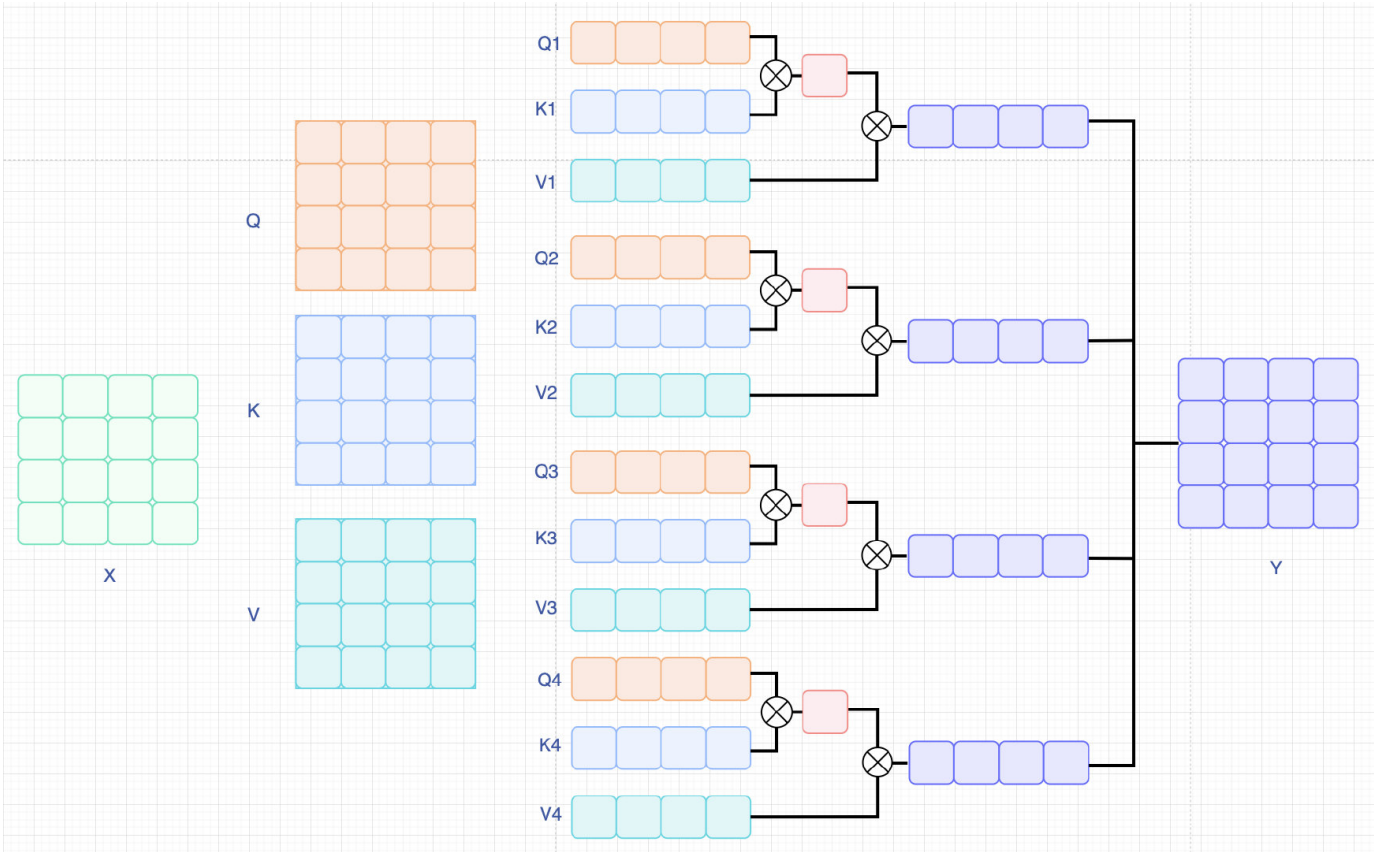


Sparse Self-Attention, 所以有了OpenAI的Sparse self-attention，直接合并Local和Atrous，除了相对距离不超过k的，相对距离为k的倍数的注意力都为0，这样Attention就有了"局部紧密相关和远程稀疏相关"的特性。

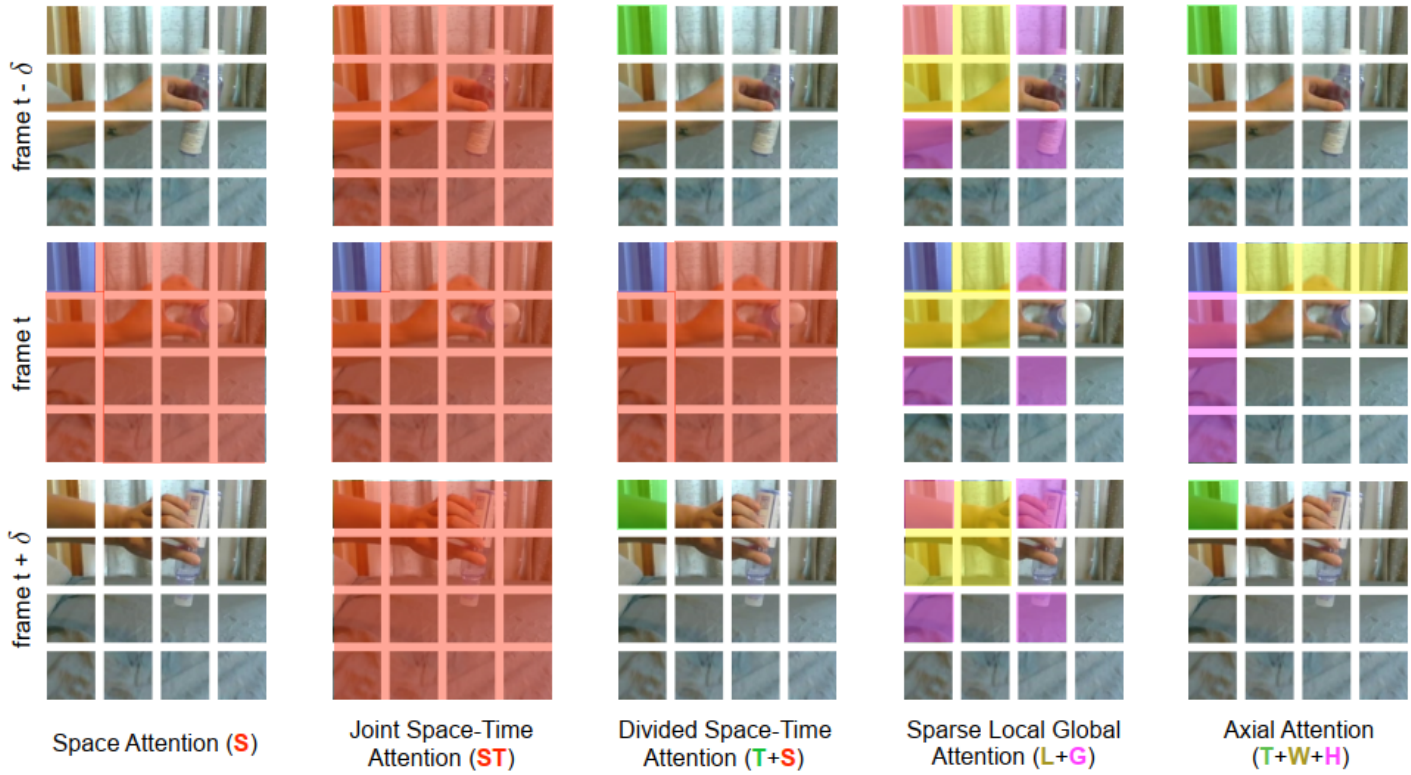


回到本文，local-attention只考虑$F \times H/2 \times W/2$的patches，也就是每个patch只关注1/4图像区域近邻的patchs，其他的patchs忽略。global-attention则采用2的stride来在Temporal维度和HW维度上进行patches的滑窗计算。与Sparser self-attention不同点在于，Sparse Local Global Attention先计算local后再进行计算global。

- **Axial Attention(T+W+H)**, 已经有很多的图像分类的paper讲过解耦attention，也就是用H或者W方向的attention单独计算，例如cswin-transformers里面的简单图示如下：



与之不同的是，Video不仅分行和列，还要分时序维度来进行计算，对应Q,K,V的weighis也各不相同。先计算Temporal-attention，然后Width-attention，最后Height-attention。行和列可以互换，不影响结果。



为了说明问题，用蓝色表示query patch，非蓝色的颜色表示在每种不同范式下与蓝色patch的自我注意力计算，不同颜色表示不同的维度来计算attention。

四、代码分析

论文中只给出了前三种attention的实现，所以我们就只分析前三种attention的code

PatchEmbed

Video的输入前面有介绍，是(B,C,T,H,W), 如果我们使用2d卷积的话，是没办法输入5个维度的，所以要合并F和B成一个维度，有(B,C,T,H,W)->((B,T),C,H,W)。和VIT一样，采用Conv2d做embeeding，代码如下，最终返回一个维度为((B,T), (H//P*W//P), D)的embeeding.

```
class PatchEmbed(nn.Module):
    """ Image to Patch Embedding
    """
    def __init__(self, img_size=224, patch_size=16, in_chans=3, embed_dim=768):
        super().__init__()
        img_size = to_2tuple(img_size)
        patch_size = to_2tuple(patch_size)
        num_patches = (img_size[1] // patch_size[1]) * (img_size[0] // patch_size[0])
        self.img_size = img_size
        self.patch_size = patch_size
        self.num_patches = num_patches

        self.proj = nn.Conv2d(in_chans, embed_dim, kernel_size=patch_size, stride=patch_size)

    def forward(self, x):
        B, C, T, H, W = x.shape
        x = rearrange(x, 'b c t h w -> (b t) c h w')
        x = self.proj(x)   # ((bt), dim, h//p, w//p)
        W = x.size(-1)
        x = x.flatten(2).transpose(1, 2)   # ((b, t), )
        return x, T, W                     # ((b, t), h//p * w//p, dims)
```

从patchEmbed得到的((B,T), nums_patches, dim),需要concat上一个clstoken用于最后的分类，所以有:

```
B = x.shape[0]
x, T, W = self.patch_embed(x)
cls_tokens = self.cls_token.expand(x.size(0), -1, -1)    #  ((bs, T), 1, dims)
x = torch.cat((cls_tokens, x), dim=1)                    #  ((bs, T), (nums+1), dims)
```

Space Attention

Space Attention已经介绍过了，只计算空间维度的atttention, 所以得到的embeeding直接送入到VIT的block里面。由于，T是合并到了BatchSize维度的，所以计算完attention后需要transpose回来，然后多帧取平均，最后送入MLP来做分类，代码如下:

```
## Attention blocks
def blocks(x):
    x = x + self.drop_path(self.attn(self.norm1(x)))
    x = x + self.drop_path(self.mlp(self.norm2(x)))
    return x

for blk in self.blocks:
    x = blk(x, B, T, W)

### Predictions for space-only baseline
if self.attention_type == 'space_only':
    x = rearrange(x, '(b t) n m -> b t n m',b=B,t=T)
    x = torch.mean(x, 1) # averaging predictions for every frame
```

Joint Space-Time Attention

Joint Space-Time Attention 需要引入 `TimeEmbeeding` , 这个Embeeidng和PosEmbeeding类似，是可学习的，定义如下：

```
self.time_embed = nn.Parameter(torch.zeros(1, num_frames, embed_dim))
```

计算attention之前，需要引入 `TimeEmbeeding` 的信息到 `PatchEmbeeding` ,所以有:

```
cls_tokens = x[:B, 0, :].unsqueeze(1)               # (bs, 1, dims)
x = x[:,1:]                                         # ((bs, t), nums_patchs, dims)
x = rearrange(x, '(b t) n m -> (b n) t m',b=B,t=T)  # ((bs, nums_patches), t, dims)
x = x + self.time_embed                          # ((bs, nums_patches), t, dims)
# 为了加上timeembeeding
x = self.time_drop(x)
x = rearrange(x, '(b n) t m -> b (n t) m',b=B,t=T) # (bs, (nums_patches, t), dims)
x = torch.cat((cls_tokens, x), dim=1)              # (bs, (nums_patches, t)  + 1, dims)
```

由于已经合并了time和space的token计算，所以直接取cls-token进行分类即可。

```
## Attention blocks
for blk in self.blocks:
    x = blk(x, B, T, W)
```

Divided Space-Time Attention

Divided Space-Time Attention相对复杂一些，涉及比较多的shape转换。和Joint一样，也需要引入 `TimeEmbeeding` ， 和上面一致，这里就不重复了。先把维度transpose为((B, nums_patches), T, Dims)进行时序的attention计算，并加上残差, 有：

```
## Temporal
xt = x[:,1:,:]                                                  # (bs, (nums_pathces, T
xt = rearrange(xt, 'b (h w t) m -> (b h w) t m',b=B,h=H,w=W,t=T)  # ((bs,  nums_pathces),
res_temporal = self.drop_path(self.temporal_attn(self.temporal_norm1(xt)))  # ((bs,  nums_patho
# 渐进式学习时间特征
res_temporal = self.temporal_fc(res_temporal)                                  # (bs, (r
xt = x[:,1:,:] + res_temporal                                                  # (bs, (r
```

这里有个特殊的层 `temporal_fc` ， 文章中并没有提到过，但是作者在github的issue有回答，temporal_fc层首先以零权重初始化，因此在最初的训练迭代中，模型只利用空间信息。随着训练的进行，该模型会逐渐学会纳入时间信息。实验表明，这是一种训练TimeSformer的有效方法。(**Note**: 训练trick，没有的话可能会掉点)

```
temporal_fc = nn.Linear(dim, dim)

nn.init.constant_(temporal_fc.weight, 0)
nn.init.constant_(temporal_fc.bias, 0)
```

然后计算空间attention，这里要注意的是需要repeat和transpose cls-token的shape，原始的cls-token只表达spatial的所有信息，现在需要把temporal的信息融合进来，代码如下：

```
## Spatial
init_cls_token = x[:,0,:].unsqueeze(1)                                          # (bs, 1,
cls_token = init_cls_token.repeat(1, T, 1)                                      # (bs, T,
cls_token = rearrange(cls_token, 'b t m -> (b t) m', b=B, t=T).unsqueeze(1)      # ((bs, 1
xs = xt
xs = rearrange(xs, 'b (h w t) m -> (b t) (h w) m',b=B,h=H,w=W,t=T)               # ((bs, 1
xs = torch.cat((cls_token, xs), 1)                                              # ((bs, 1
res_spatial = self.drop_path(self.attn(self.norm1(xs)))                         # ((bs, 1
```

cls-token这里有两个作用，一个是保留原始特征信息并参与空间特征计算，另一个是融合时序特征。

```
### Taking care of CLS token
cls_token = res_spatial[:,0,:]                                                  # ((bs,
cls_token = rearrange(cls_token, '(b t) m -> b t m',b=B,t=T)                    # (bs, T,
cls_token = torch.mean(cls_token,1,True) ## averaging for every frame          # (bs, 1,
res_spatial = res_spatial[:,1:,:]                                               # ((bs, 1
res_spatial = rearrange(res_spatial, '(b t) (h w) m -> b (h w t) m',b=B,h=H,w=W,t=T)  # (bs, (r
res = res_spatial
x = xt
```

第一部分就是带有原始cls-token的时序残差特征，第二部分就是融合时序特征的空间cls-token和spatial-attention，两部分相加，最后送入MLP，完成整个attention的计算。

```
# res
x = torch.cat((init_cls_token, x), 1) + torch.cat((cls_token, res), 1)          # (bs, (r
## Mlp
x = x + self.drop_path(self.mlp(self.norm2(x)))
```

五、实验结果

- **Analysis of Self-Attention Schemes**

Attention	Params	K400	SSv2
Space	85.9M	76.9	36.6
Joint Space-Time	85.9M	77.4	58.5
Divided Space-Time	121.4M	**78.0**	**59.5**
Sparse Local Global	121.4M	75.9	56.3
Axial	156.8M	73.5	56.2

Table 1. Video-level accuracy for different space-time attention schemes in TimeSformer. We evaluate the models on the validation sets of Kinetics-400 (K400), and Something-Something-V2 (SSv2). We observe that divided space-time attention achieves the best results on both datasets.

Attention实验结论很明显，K400和SSV2，Divided Space-Time效果是最好的, 比较有趣的是Space在K400的表现并不差，但是在SSV2上效果很差，说明SSV2数据集更加趋向于动作，K400更加趋向于内容。（**NOTE**: Joint Space-Time attention实际上使用了TimeEmbeeding的，实际参数量应该比Space多一点点，不过量级很少，所以这里没有标示。）

- **compare the computational cost**

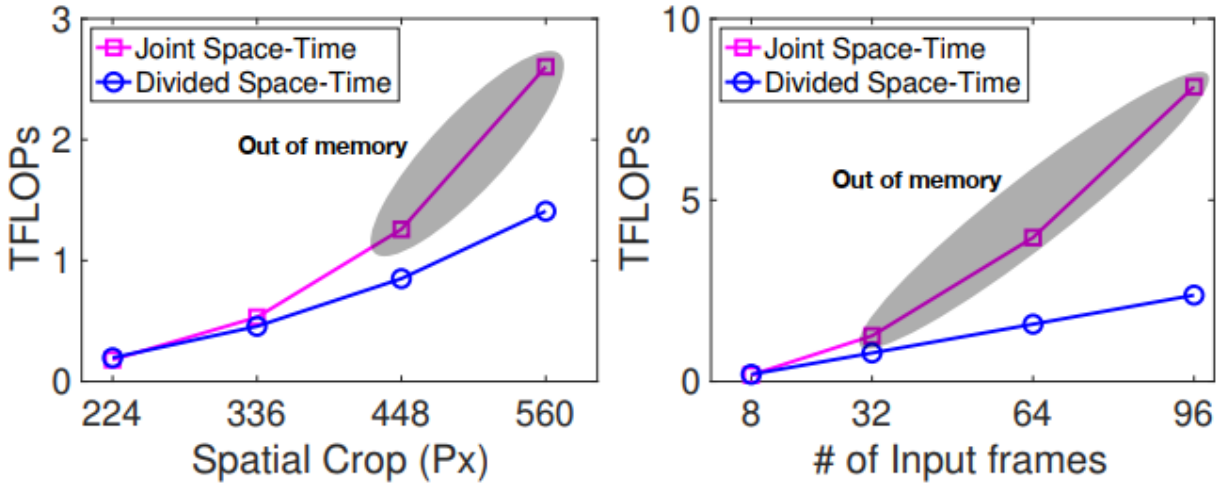


Figure 3. We compare the video classification cost (in TFLOPs) of Joint Space-Time versus Divided Space-Time attention. We plot the number of TFLOPs as a function of spatial crop size in pixels (left), and the number of input frames (right). As we increase the spatial resolution (left), or the video length (right), our proposed divided space-time attention leads to dramatic computational savings compared to the scheme of joint space-time attention.

做了一下极限crop和frames的实验，可以看到Divided Space-time可以跑更大的分辨率且更多的帧，也就意味着可以刷更高的指标。

- **Comparison to 3D CNNs**

Model	Pretrain	K400 Training Time (hours)	K400 Acc.	Inference TFLOPs	Params
I3D 8x8 R50	ImageNet-1K	444	71.0	1.11	28.0M
I3D 8x8 R50	ImageNet-1K	1440	73.4	1.11	28.0M
SlowFast R50	ImageNet-1K	448	70.0	1.97	34.6M
SlowFast R50	ImageNet-1K	3840	75.6	1.97	34.6M
SlowFast R50	N/A	6336	76.4	1.97	34.6M
TimeSformer	ImageNet-1K	**416**	75.8	**0.59**	121.4M
TimeSformer	ImageNet-21K	**416**	**78.0**	**0.59**	121.4M

Table 2. Comparing TimeSformer to SlowFast and I3D. We observe that TimeSformer has lower inference cost despite having a larger number of parameters. Furthermore, the cost of training TimeSformer on video data is much lower compared to SlowFast and I3D, even when all models are pretrained on ImageNet-1K.

虽然TimeSformer的参数很大，但是推理开销更少，训练成本也更低，反之I3D，SlowFast这种3D CNNs需要更长的优化周期才能达到不错的性能。

- **The Importance of Pretraining**

Method	Pretraining	K400	SSv2
TimeSformer	ImageNet-1K	75.8	**59.5**
TimeSformer	ImageNet-21K	**78.0**	**59.5**
TimeSformer-HR	ImageNet-1K	77.8	62.2
TimeSformer-HR	ImageNet-21K	**79.7**	**62.5**
TimeSformer-L	ImageNet-1K	78.1	**62.4**
TimeSformer-L	ImageNet-21K	**80.7**	62.3

Table 3. Comparing the effectiveness of ImageNet-1K and ImageNet-21K pretraining on Kinetics-400 (K400) and Something-Something-V2 (SSv2). On K400, ImageNet-21K pretraining leads consistently to a better performance compared to ImageNet-1K pretraining. On SSv2, ImageNet-1K and ImageNet-21K pretrainings lead to similar accuracy.

实验说明了一个问题，更NB的pretrain会带来更高的收益， `TimeSformer` 表示的是 `8x224x224` video片段输入， `TimeSformer-HR` 表示的是 `16x448x448` video片段输入， `TimeSformer-L` 表示的是 `96x224x224` video片段输入。

- **The Impact of Video-Data Scale**

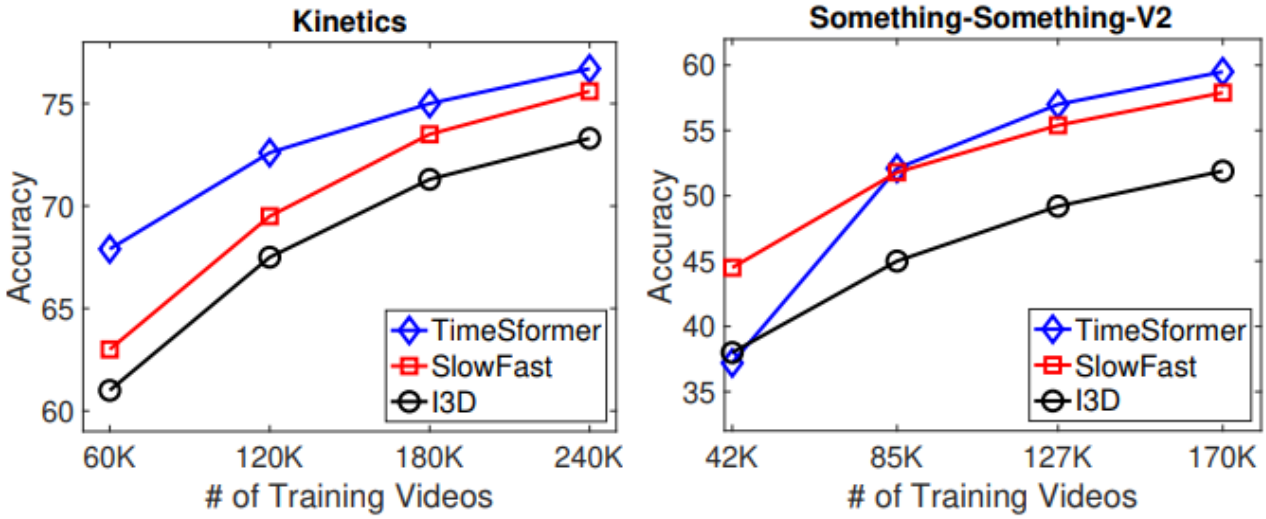


Figure 4. Accuracy on Kinetics-400 (K400), and Something-Something-V2 (SSv2) as a function of the number of training videos. On K400, TimeSformer performs best in all cases. On SSv2, which requires more complex temporal reasoning, TimeSformer outperforms the other models only when using enough training videos. All models are pretrained on ImageNet-1K.

分开讨论，对于理解性的视频数据集，K400，TimeSfomer可以在少量数据集的情况下也超过I3D和SlowFast。对于时序性的数据，TimeSformer需要更多的数据集才能达到不错的效果。

- **The Importance of Positional Embeddings**

Positional Embedding	K400	SSv2
None	75.4	45.8
Space-only	77.8	52.5
Space-Time	**78.0**	**59.5**

Table 4. Ablation on positional embeddings. The version of TimeSformer using space-time positional embeddings yields the highest accuracy on both Kinetics-400 and SSv2.

空间和时序的pos embeeding很重要，尤其是SSV2数据集上表现很明显。

- **Varying the Number of Tokens**

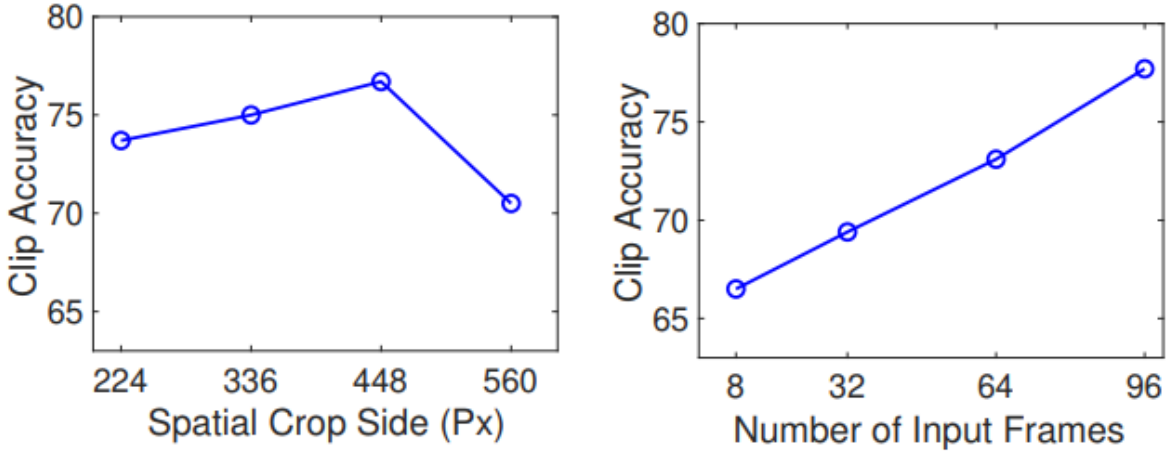


Figure 5. Clip-level accuracy on Kinetics-400 as a function of spatial crop size in pixels (left), and the number of input frames (right).

增加分辨率可以提升性能，增加视频采样帧数可以带来持续收益，最高可以达到96帧(GPU显存限制)，已经远超cnn base的8-32帧。

- **Comparison to the State-of-the-Art**

Method	Top-1	Top-5	TFLOPs
R(2+1)D (Tran et al., 2018)	72.0	90.0	17.5
bLVNet (Fan et al., 2019)	73.5	91.2	0.84
TSM (Lin et al., 2019)	74.7	N/A	N/A
S3D-G (Xie et al., 2018)	74.7	93.4	N/A
Oct-I3D+NL (Chen et al., 2019)	75.7	N/A	0.84
D3D (Stroud et al., 2020)	75.9	N/A	N/A
I3D+NL (Wang et al., 2018b)	77.7	93.3	10.8
ip-CSN-152 (Tran et al., 2019)	77.8	92.8	3.2
CorrNet (Wang et al., 2020a)	79.2	N/A	6.7
LGD-3D-101 (Qiu et al., 2019)	79.4	94.4	N/A
SlowFast (Feichtenhofer et al., 2019b)	79.8	93.9	7.0
X3D-XXL (Feichtenhofer, 2020)	80.4	94.6	5.8
TimeSformer	78.0	93.7	**0.59**
TimeSformer-HR	79.7	94.4	5.11
TimeSformer-L	**80.7**	**94.7**	7.14

Table 5. Video-level accuracy on Kinetics-400.

Method	Top-1	Top-5
I3D-R50+Cell (Wang et al., 2020c)	79.8	94.4
LGD-3D-101 (Qiu et al., 2019)	81.5	95.6
SlowFast (Feichtenhofer et al., 2019b)	81.8	95.1
X3D-XL (Feichtenhofer, 2020)	81.9	95.5
TimeSformer	79.1	94.4
TimeSformer-HR	81.8	**95.8**
TimeSformer-L	**82.2**	95.6

Table 6. Video-level accuracy on Kinetics-600.

K400, TimeSformer采用的是3spatial crops(left,center,right)就可以达到80.7%的SOTA。K600，TimeSformer达到了82.2%的SOTA。

- **The effect of using multiple temporal clips**

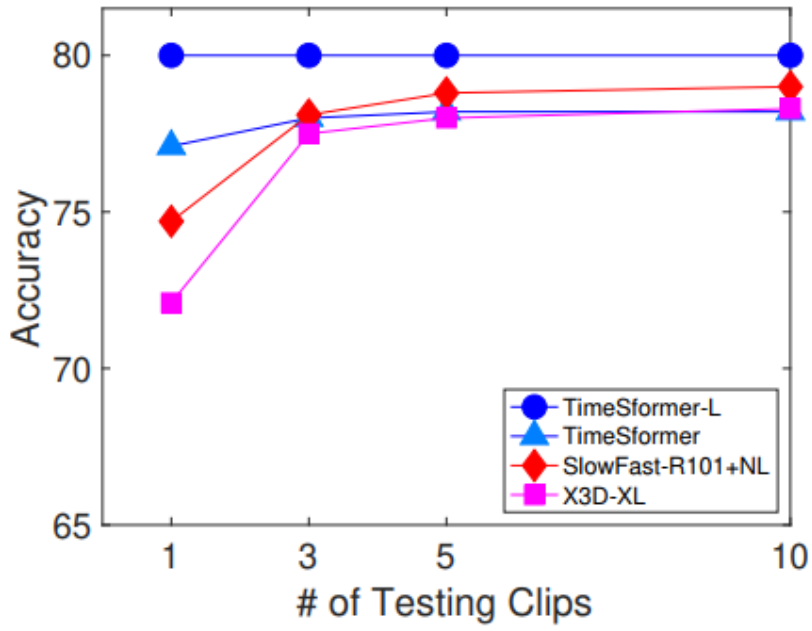


Figure 6. Video-level accuracy on Kinetics-400 vs the number of temporal clips used during inference. TimeSformer-L achieves excellent accuracy using a small number of clips, which leads to strong performance at low inference cost.

采用了{1,3,5,10}不同的clips数量，可以看到TimeSfomer-L的性能保持不变，TimeSfomer在3clips的时候性能保持稳定，X3D,SlowFast还会随着clips的增加(>=5)而提升性能。对于略短的视频片段来说，TimeSfomer可以用更少的推理开销达到很高的性能。

- **Something-Something-V2 & Diving-48**

Method	SSv2	Diving-48**
SlowFast (Feichtenhofer et al., 2019b)	61.7	77.6
TSM (Lin et al., 2019)	63.4	N/A
STM (Jiang et al., 2019)	64.2	N/A
MSNet (Kwon et al., 2020)	64.7	N/A
TEA (Li et al., 2020b)	65.1	N/A
bLVNet (Fan et al., 2019)	**65.2**	N/A
TimeSformer	59.5	74.9
TimeSformer-HR	62.2	78.0
TimeSformer-L	62.4	**81.0**

Table 7. Video-level accuracy on Something-Something-V2 and Diving-48. **Due to an issue with Diving-48 labels used in previously published results, we only compare our method with a reproduced SlowFast **16** $\times$ **8** R101 model. All models are pretained on ImageNet-1K.

SSV2上的性能只比SlowFast高，甚至低于TSM，Diviing-48比SlowFast高了很多。

- **Long-Term Video Modeling**

Method	# Input Frames	Single Clip Coverage	# Test Clips	Top-1 Acc
SlowFast	8	8.5s	48	48.2
SlowFast	32	34.1s	12	50.8
SlowFast	64	68.3s	6	51.5
SlowFast	96	102.4s	4	51.2
TimeSformer	8	8.5s	48	56.8
TimeSformer	32	34.1s	12	61.2
TimeSformer	64	68.3s	6	62.2
TimeSformer	96	102.4s	4	**62.6**

Table 8. Long-term task classification on HowTo100M. Given a video spanning several minutes, the goal is to predict the long-term task demonstrated in the video (e.g., cooking breakfast, cleaning house, etc). We evaluate a few variants of SlowFast and TimeSformer on this task. "Single Clip Coverage" denotes the number of seconds spanned by a single clip. "# Test Clips" is the average number of clips needed to cover the entire video during inference. All models in this comparison are pretrained on Kinetics-400.

相比于SlowFast在长视频的表现，TimeSformer高出10个点左右，这个表里的数据是先用k400做pretrain后训练howto100得到的，使用imagenet21k做pretrain，最高可以达到62.1%，说明TimeSformer可以有效的训练长视频，不需要额外的pretrian数据。

- **Additional Ablations**

1. Smaller&Larger Transformers
   Vit Large, k400和SSV2都降了1个点 相比vit base
   Vit Small, k400和SSV2都降了5个点 相比vit base
2. Larger Patch Size
   patchsize 从16调整为32，降低了3个点
3. The Order of Space and Time Self-Attention
   调整空间attention在前，时序attention在后，降低了0.5个点
   尝试了并行时序空间attention，降低了0.4个点

- **Visualizing Learned Space-Time Attention**

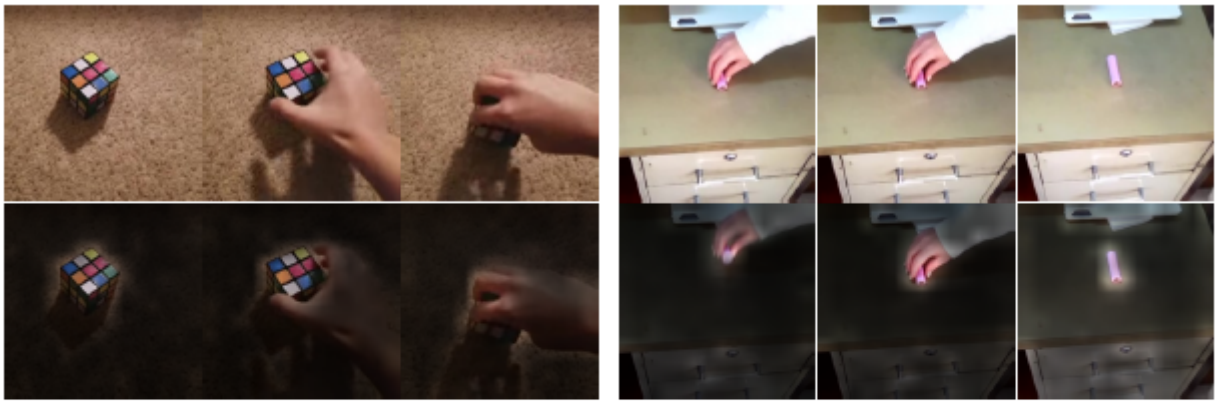


Figure 7. Visualization of space-time attention from the output token to the input space on Something-Something-V2. Our model learns to focus on the relevant parts in the video in order to perform spatiotemporal reasoning.

TimeSformer可以学会关注视频中的空间和时序相关部分，以便进行时空理解。

- **Visualizing Learned Feature Embeddings.**

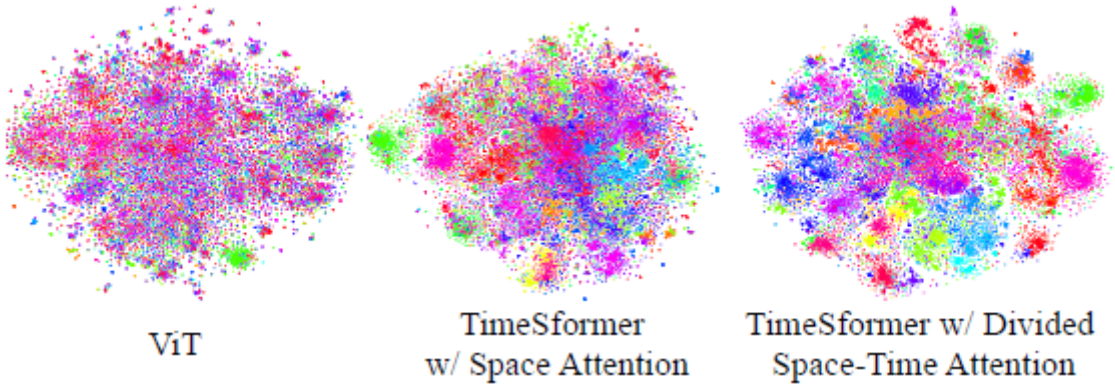


Figure 8. Feature visualization with t-SNE (van der Maaten & Hinton, 2008) on Something-Something-V2. Each video is visualized as a point. Videos belonging to the same action category have the same color. The TimeSformer with divided space-time attention learns semantically more separable features than the TimeSformer with space-only attention or ViT (Dosovitskiy et al., 2020).

t-SNE显示，可以看到Divided Space-Time Attention的特征区分程度更强

六、结论

- 提出了基于Transformer的video模型范式，设计了divide sapce-time attention。
- 在K400,K600上取得了SOTA的效果。
- 相比于3D CNNs，训练和推理的成本低。
- 可以应用于超过一分钟的视频片段，具备长视频建模能力。

参考

- https://blog.csdn.net/m0_37531129/article/details/108125010
- https://arxiv.org/pdf/1904.10509.pdf