Temporal Transductive Inference for Few-Shot Video Object Segmentation

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Abstract

Few-shot video object segmentation (FS-VOS) aims at segmenting video frames using a few labelled examples of classes not seen during initial training. In this paper, we present a simple but effective temporal transductive inference (TTI) approach that leverages temporal consistency in the unlabelled video frames during few-shot inference without episodic training. Key to our approach is the use of a video-level temporal constraint that augments frame-level constraints. The objective of the video-level constraint is to learn consistent linear classifiers for novel classes across the image sequence. It acts as a spatiotemporal regularizer during the transductive inference to increase temporal coherence and reduce overfitting on the few-shot support set. Empirically, our approach outperforms state-of-the-art meta-learning approaches in terms of mean intersection over union on YouTube-VIS by 2.5%. In addition, we introduce an improved benchmark dataset that is exhaustively labelled (i.e., all object occurrences are labelled, unlike the currently available). Our empirical results and temporal consistency analysis confirm the added benefits of the proposed spatiotemporal regularizer to improve temporal coherence.

Keywords

few-shot learning; transductive inference; video object segmentation

1 Introduction

1.1 Motivation

Few-shot object segmentation is concerned with demarking novel classes in static images (i.e. the query set) aided with a few labelled images containing the novel classes (i.e. the support set) [26,41,35,40,28,17,38,1]. Most approaches follow a meta-learning scheme that emulates the inference stage during training through sampling tasks of support and query sets (i.e., episodic training).

Similar to few-shot object segmentation, few-shot video object segmentation (FS-VOS) segments objects in query videos with novel classes specified by a support set of images. Compared to few-shot single image segmentation, FS-VOS has received limited attention [27,5].

Meta-learning has been widely explored in few-shot learning [29,33,38,41]. Even so, recent work has pointed out issues in the applicability of meta-learning to the few-shot setting [6,1]. Transductive inference has emerged as a viable means to address some of these issues [32,21,7,11,15,2]. Within the context of few-shot single image segmentation, recent work has shown that transductive inference can lead to surpassing the performance of non-transductive approaches [1]. In particular, superior performance came about via use of the prediction statistics of the unlabelled query imagery to regularize the learning of linear classifiers for the novel classes. In general, transductive inference uses the few-shot labelled support set along with the unlabelled query images to refine the learning of classifiers for novel classes [7] and classifies the query set as a whole at once [2].

A naive extension of the transductive approach for single image object segmentation to few-shot video object segmentation learns a single classifier for each novel class on the entire video. However, we demonstrate in our experiments that regularization using the unlabelled query imagery fails
Few-Shot Video Object Segmentation

Support Set

Query Set Video Predictions: Single Image Baseline

Query Set Video Predictions: Our Spatiotemporal Regularizers

Keyframe Refinement

Globally consistent set of independent classifiers per-frame

Fig. 1: Overview of our temporal transductive inference (TTI) for FS-VOS. For each novel class, we learn an independent set of per-frame linear classifiers using the cross entropy loss on the support set and foreground/background region proportion regularization on the unlabelled query frames. We present a set of spatiotemporal regularizers, including a global constraint that ensures a consistent set of linear classifiers on the video level, $L_{\text{global}}$, and a keyframe refinement that dynamically selects the frame closest to the video-level prototype to be used for refinement. Top: support set. Middle: query predictions for our single image baseline. Bottom: query predictions for our approach. The support set ground truth and query predictions are highlighted in red.

1.2 Contributions

Overall, our contributions are threefold. (i) We present a novel temporal transductive inference (TTI) approach that does not require episodic training and enforces global temporal consistency to regularize the learning of the classifiers with few-shot labelled examples. To the best of our knowledge, no previous research has used transductive fine-tuning for few-shot video segmentation. (ii) We introduce a novel keyframe-based fine-tuning of classifier weights during training. This approach allows the well segmented frames in a video to guide the training of other frames. Moreover, it avoids expensive on-line backbone fine-tuning, yet yields superior results. (iii) We improve the previously proposed FS-VOS evaluation protocol by building an exhaustively labelled FS-VOS benchmark, called MiniVSPW. Moreover, we evaluate the temporal consistency of our predictions using video consistency, which was lacking previously. Our code and datasets are publicly available at https://github.com/MSiam/tti_fsvos.
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2 Related work

2.1 Few-shot object segmentation

Most few-shot segmentation approaches are metric learning based. They mainly differ in how the support set is used to guide few-shot models, e.g., using a single vector representation from masked average pooling [24, 41, 35], co-attention [27, 39], multiscale feature enrichment [30] or graph neural networks [40]. Others explore a more powerful representation than what is afforded by a single prototype (i.e., class representative), e.g., use of part-aware prototypes [17] or prototype mixtures [28].

A major focus in the few-shot literature has been meta-learning. A major drawback of meta-learning approaches is their sensitivity to changes in the cardinality of the support set between training and testing [1, 3]. Transductive inference has been studied in the context of few-shot classification [16, 21, 17, 23], and was shown to have superior performance over meta-learning. Most closely related to our work is a single image classification approach that leveraged unlabelled query images to regularize fine-tuning of the final classifiers [11]. Notably, all these previous efforts focused on static images without considering temporal constraints available in video. We address this gap and present a novel temporal transductive inference approach via use of spatiotemporal regularizers.

2.2 Video Segmentation

Video segmentation (VS) trained on large-scale labelled datasets has been investigated heavily [35]. There are three main categories of approaches. (i) Automatic video object segmentation (VOS) segments objects that are visually salient on the basis of motion and/or appearance in an image sequence [10, 31]. (ii) Semi-automatic VOS relies on an initial labelled frame and subsequently tracks and segments the initialized objects throughout the sequence [42, 18]. (iii) Semantic VS is concerned with segmenting a finite set of semantic categories that are learned during training [8, 19].

Both semi-automatic and automatic VOS are decidedly different from few-shot video segmentation. Semi-automatic VOS is provided with masks for the same objects in the sequence for subsequent tracking. FS-VOS is more challenging, as it uses a support set defined by imagery independent of the tracking video. The support set can be significantly different from the query video in terms of object properties (e.g. different dog breeds, color and texture) as well as different viewing conditions (e.g. viewpoint, lighting and occlusion). Therefore, the latter can easily suffer from overfitting and needs to be equipped with specific strategies to generalize to novel classes from few labelled examples. As for automatic VOS, while it does not rely on an initial labelled frame, it can not be guided to segment certain semantic categories. In contrast, FS-VOS can exploit its support set to guide what classes are of specific interest. Overall, the FS-VOS task can be seen as the few-shot counterpart of video semantic segmentation that segments novel unseen classes beyond the finite set of classes used in training.

Temporal continuity constraints have proven useful in VOS [56]. Semi-automatic VOS approaches have used unlabelled frames transductively to enforce temporal continuity [42, 18]. Earlier work on video semantic segmentation applied representation warping to fuse features from consecutive frames to ensure temporal consistency of the predictions in an inductive setting [8]. Unlike previous work, we focus on transductive inference for few-shot video segmentation.

2.3 Few-shot video object segmentation

Compared to video segmentation and few-shot segmentation with static imagery, there has been limited work on few-shot video object segmentation (FS-VOS). Recent efforts focused on exploring attention [27, 5]. Co-attention conditioned on visual as well as semantic features was proposed and evaluated using a protocol that did not maintain the same support set on the entire sequence [27]. The other effort factorized full-rank many-to-many attention into two smaller components and proposed an evaluation protocol that used a single support set for the entire sequence [5]. All these approaches are meta-learning-based and thereby inherit the aforementioned meta-learning drawbacks. In contrast, we explore temporal transductive inference. Additionally, we introduce a new benchmark that addresses limitations in what was available previously [5].

3 Technical approach

3.1 Problem formulation

We formulate Few-Shot Video Object Segmentation (FS-VOS) as follows, cf. [5]. Let \( D_{\text{train}} \) and \( D_{\text{test}} \) be training and testing data, resp. For a dataset with \( C \) categories, split into \( O \) folds, each fold will have \( \frac{C}{O} \) categories that comprise the novel test set, \( C_{\text{test}} \), while the remaining \( C - \frac{C}{O} \) categories are used as base classes, \( C_{\text{train}} \), for training, with \( C_{\text{train}} \cap C_{\text{test}} = \emptyset \). Classes in \( C_{\text{train}} \) are represented with multiple instances in \( D_{\text{train}} \). For training, we train the model in a standard manner on the base classes. For few-shot inference, we use episodic evaluation, where \( N_e \) tasks are sampled from \( D_{\text{test}} \) with support and query set pairs \( \{ S_i, Q_i \}_{i=1}^{N_e} \). The support set in a one-way K-shot task has \( K \) image-label pairs \( S = \{ X_k^{(s)}, M_k^{(s)} \}_{k=1}^{K} \), where superscript, \((s)\), denotes support set and \( M_k^{(s)} \) is a binary segmentation mask.
for a class of interest in $C_{\text{text}}$. The image-label pairs $X_k, M_k \in \mathbb{R}^{W \times H \times 3}, \mathbb{R}^{W \times H}$, with $W \times H$ spatial dimensions. The few-shot models are then required to separate the class of interest from the background, hence the one-way evaluation. The query set has consecutive frames sampled from a video $Q = \{X_i^{(q)}\}_{i=1}^{N_q}$, where superscript, $(q)$, denotes query set and $N_q$ is the number of frames.

### 3.2 Preliminaries

In few-shot inference, the backbone model weights, $\theta$, are taken as fixed and linear classifier weights, $\omega^l$, and biases, $b^l$, are learned for the novel classes, where $l$ stands for the optimization iteration. We are given a pair of support and query sets, $(S, Q)$, as defined above. Inspired by weight imprinting methods, built on the relation between softmax classification and metric learning \cite{22, 28}, we consider the final classifier weights as class prototypes.

The extracted features, using the backbone, $f_0$, from the support sets are defined as $F_k^{(s)} = f_0(X_k^{(s)})$ and normalized according to $\hat{F}_k^{(s)} = \frac{F_k^{(s)}}{\|F_k^{(s)}\|}$, and similarly for $F_t^{(q)}$. The novel class weights are initialized (imprinted) to the extracted prototype from the support set features according to

$$\omega^0 = \frac{1}{K} \sum_{k=1}^{K} \sum_{x,y} M_k^{(s)}(x, y) \hat{F}_k^{(s)}(x, y),$$

where $x, y$ are the spatial locations. For the sake of compactness of notation, throughout the rest of the paper we only use superscript $(s)$ when denoting the support set; otherwise, it is considered the query without the need for the additional superscript. Biases are initialized to the average of the initial foreground predictions on the query set $\{1\}$, $p_{f_g}^{(0)}$, according to

$$b^0 = \frac{1}{WH} \sum_{x,y} p_{f_g}^{(0)}(x, y).$$

We then estimate the per-pixel probabilities for belonging to the sampled class in the one-way task or background according to

$$p_i^{(x, y)} = \frac{(1 - \sigma^l(x, y))}{\sigma^l(x, y)},$$

where $\sigma^l(x, y) = \text{sigmoid}(\tau((F(x, y), \omega^l) - b^l))$ with $\langle \cdot, \cdot \rangle$ denoting cosine similarity and $\tau$ a constant hyperparameter for scaling the output, of $\{1\}$. The formulation, \cite{1}, can lead to degenerate solutions. Previous single image object segmentation work has considered the foreground/background region proportion as a constraint; however, it is only applied to individual images \cite{1}. We instead propose constraints that take temporal consistency into account, as natural for video object segmentation.

We present a novel temporal transductive inference approach to FS-VOS that exploits the temporal constraints inherent in unlabelled query video frames. In doing so, we introduce a global temporal video-level constraint that contributes to the training loss by leveraging temporal relations in the query set. This global constraint encourages consistency to the learned prototype at the video level. Our proposed algorithm is shown in Figure 2. In the following subsections, we define our global constraint and the final two-stage learning scheme.

### 3.3 Global temporal consistency

Our global consistency constraint operates by encouraging frame-wise query signatures to be consistent with video-wise prototypes. We calculate foreground, $z_{f_g}^{(t)}$, and background, $z_{b_g}^{(t)}$, signatures at iteration $t$ for individual query frames in the form of soft masked average pooling according to

$$z_{f_g}^{(t)} = \frac{\sum_{x,y} p_{f_g}^{(t)}(x, y) \hat{F}(x, y)}{\sum_{x,y} p_{f_g}^{(t)}(x, y)},$$

$$z_{b_g}^{(t)} = \frac{\sum_{x,y} p_{b_g}^{(t)}(x, y) \hat{F}(x, y)}{\sum_{x,y} p_{b_g}^{(t)}(x, y)},$$

resp., with $F = f_0(X)$, $\hat{F} = \frac{F}{\|F\|}$ and $p_{f_g}^{(t)}(x, y), p_{b_g}^{(t)}(x, y)$ calculated analogous to \cite{3}. These query foreground and background signatures act as a representative of what is classified as foreground or background based on the current set of weights.

For a sequence, $v$, with $N_v$ frames, we calculate on the sequence level a global prototype

$$\Omega_v^t = \frac{1}{N_v} \sum_{t=1}^{N_v} \omega^l(t),$$

The linear classifier weights can be trained using the cross entropy loss on the few-shot support set.

$$L_{ce} = -\frac{1}{K} \sum_{k=1}^{K} \frac{1}{WH} \sum_{x,y} \hat{M}_k^{(s)}(x, y) \log p_k^{(s)}(x, y),$$

where $\hat{M}_k^{(s)}$ is defined as the one-hot vector of the segmentation mask. By itself, i.e. without additional constraints, this formulation can lead to degenerate solutions. Previous single image object segmentation work has considered the foreground/background region proportion as a constraint; however, it is only applied to individual images \cite{1}. We instead propose constraints that take temporal consistency into account, as natural for video object segmentation.
Fig. 2: Overview of our temporal transductive inference algorithm. Features are extracted from images using a backbone architecture, $f_\theta$, from which linear classifier weights, $w_l$, and biases, $b_l$, are optimized for each frame, $t$, at each iteration, $l$. This optimization is performed in two stages. The first stage uses a cross entropy loss, $L_{ce}$, with respect to the support set. Global consistency is enforced via a constraint, $L_{global}$, that drives per query frame foreground signatures, $z_{fg}^l$, closer to the video global prototype, $\Omega^l_{global}$, and further apart from the background signatures, $z_{bg}^l$, (visualized on a unit hypersphere). Additional constraints, $L_H$ and $L_{KL}$, increase prediction confidence and avoid focusing on too small regions using (8) and (9), resp. The second stage selects a keyframe, (13), based on the closest query frame signature, $z_{fg}^l$, to the final video-level prototype, $\Omega^L_{global}$. This selection is followed by weight refinement using the keyframe.

The prototype, $\Omega^l_{global}$, is computed with every optimization iteration, $l$. We then use the signatures, (5), to regularize the learning for both weights and biases of novel classes to be consistent on the sequence level with the global prototype, (6). Thus, our temporal constraint is formulated as a transductive loss according to

$$L_{global} = \frac{1}{N_v} \sum_{t=1}^{N_v} 1 - \langle \Omega^l_{global}, z_{fg}^l(t) \rangle + \frac{1}{N_v} \sum_{t=1}^{N_v} \max(0, \langle \Omega^l_{global}, z_{bg}^l(t) \rangle),$$

where $\langle \cdot, \cdot \rangle$ denotes cosine similarity. This global loss, (7), leads to maximizing the cosine similarity between the foreground signature of frame $t$, $z_{fg}^l(t)$, and the global prototype, $\Omega^l_{global}$, while pushing it further away from the estimated background signature, $z_{bg}^l(t)$. We use $\max(0, \cdot)$ to avoid non-negative loss.

The optimization is repeated for several iterations, $l = \{1, 2, \ldots, L\}$. For each iteration, we recompute the global prototype, $\Omega^l_{global}$, and the foreground/background signatures, $z_{fg}^l, z_{bg}^l$. This loss is motivated by the slowness principle, which entails that important characteristics of the scene tend to change slower than the per-pixel individual measurements, cf. [20]. In our case, since we seek to regularize the learning of weights and biases of the novel classes, we use the query predictions in a transductive manner to guide the extraction of foreground/background signatures per query frame. In that way, we drive the foreground signatures to be clustered together and further apart from the background signatures on the sequence level, instead of solely on consecutive frames. The learning thereby updates the linear classifier weights and biases while ensuring global consistency.

### 3.4 Additional constraints

Following previous work on single image object segmentation with transductive inference [1], we incorporate two of their constraints into our approach. The first minimizes the entropy of the query predictions to increase its confidence. The second constrains foreground/background region proportion to avoid degenerate solutions.

Regions that are predicted with medium confidence are conserved through minimization of the prediction entropy. This constraint leads to the loss

$$L_H = -\frac{1}{WH} \sum_{x,y} p(x,y)^\top \log p(x,y).$$

Degenerate solutions, e.g. arising as emphasis on too small regions in an image in the query set, are further avoided by constraining foreground/background region proportions. In particular, the model predictions on the query are constrained to follow a prior distribution, $P_\phi$, via the Kullback-Leibler (KL) divergence. This constraint is formulated as a loss

$$L_{KL} = P^l \top \log \frac{P^l}{P_\phi},$$

where $P^l = \frac{1}{WH} \sum_{x,y} p^l(x,y)$ is the label marginal distribution for the query predictions at iteration, $l$, and $P_\phi$ is estimated similarly at $l = 0$, then updated after $L_\phi$ iterations for a better estimate.
While useful in avoiding focus on too small a foreground region, our preliminary experiments with the single image baseline indicated that KL divergence loss, \( L \), is sensitive to the prior label-marginal distribution, \( P_v \). In particular, it can lead to degenerate solutions if set to an erroneous prior due to early overfitting. These degeneracies arise because the baseline model minimizes this loss on a single image. Correspondingly, it has a different foreground/background region proportion estimate per query image and the loss is calculated on every frame separately without temporal information. These difficulties are mitigated by our incorporation of a global temporal loss, \( L \).

3.5 Learning scheme

3.5.1 Training

During training on the base classes, we follow the standard FS-VOS training paradigm with image-label pairs \( D_{\text{train}} = \{X_i, M_i\}_{i=1}^{N_{\text{te}}} \). The labels, \( M_i \), are pixel-wise multi-class segmentation masks for the set of classes \( C_{\text{train}} \). Additionally, we use an auxiliary dense contrastive loss similar to previous work \[37\]. The loss is applied on temporally sampled frame pairs’ features, \( F(t), F(t + i) \), for frames \( t, t + i \) and spatial position, \( p \), extracted before spatial pyramid pooling and normalized. This manipulation helps our model learn dense matching between frame pairs without relying solely on base class labels with the loss,

\[
L_{\text{DCL}} = -\log \frac{\exp \left( \langle F_p(t), F_{p+}(t+i) \rangle \right)}{\sum_{a \in A} \exp \left( \langle F_p(t), F_{a}(t+i) \rangle \right)/\tau_d}, \tag{10}
\]

where \( F_{p}(t) \) is the anchor and \( F_{p+}(t + i) \) is the positive exemplar that is selected based on maximum cosine similarity to the anchor. Finally, the set \( A \) consists of all exemplars, and \( \tau_d \) is the temperature hyperparameter. The final training loss becomes

\[ L = L_{\text{ce}} + L_{\text{DCL}}. \tag{11} \]

3.5.2 Inference

During transductive inference, our final loss combines all terms defined above according to

\[ L = L_{\text{ce}} + \lambda_1 L_{H} + \lambda_2 L_{KL} + \lambda_3 L_{\text{global}} \tag{12} \]

where \( \lambda_i \) are empirically determined weights.

Linear classifier weights for the novel classes are optimized in two stages. (i) The weights are learned through the minimization of the final loss, \( L \), for \( L \) iterations. (ii) The weights are further optimized using the best predicted frame, \( t \), which is referred to as the keyframe in the following. This frame is selected based on the highest cosine similarity between the foreground signature at frame \( t \), \( z_{fg}(t) \), according to \[5\], and the global prototype from \[6\]. In particular, for a video, \( v \), we define its keyframe as

\[ v(t), \quad t = \text{argmax}_{t} \langle z_{fg}(t), \Omega_v^L \rangle > . \tag{13} \]

Keyframe pseudo-labels are constructed from their predictions following previous work \[53\]: A distance transform is used to select negative pixels far from the predicted positive pixels, while the remaining pixels are ignored to avoid erroneous labels. In this second stage only a cross entropy loss, analogous to \[4\], is used.

Algorithm 1: Temporal Transductive Inference (TTI) algorithm.

1: function FS-VOS INERENCE(Input: Tasks = \{\( S_i, Q_i \}_{i=1}^{N_{\text{te}}} \})
2: for \( S \rightarrow \{ \{X^{(s)}_k, M_s^{(s)}\}_{k=1}^{K}, Q = \{X^{(q)}_i\}_{i=1}^{N_{\text{te}}} \in n \}
3: \text{Tasks do}
4: \( F^{(s)} = f_0(X^{(s)}) \notin \{N_v \times C \times H \times W\} \)
5: \( F^{(s)} = f_0(X^{(s)}) \notin \{K \times C \times H \times W\} \)
6: Normalize features to get \( \hat{F}^{(s)} \).
7: Compute \( p^{L} \) using \( \{\omega^L, b^L\} \) in Eq. 3.
8: end for
9: end function
10: function TTTI(\( F^{(s)}, \hat{F}^{(s)}, M^{(s)} \))
11: Compute initial label-marginal distribution per frame \( \{P_0(t)\}_{t=1}^{T} \).
12: Initialize \( \omega^L, b^L \) using Eq. 1 and 2, resp., for each frame set \( P_0(t) = P^L(t) \).
13: for Iteration \( l \in \{1..L\} \)
14: if \( l = L \) then
15: Set \( P_{l}(t) = P^{L}(t) \).
16: end if
17: if \( l < L \) then
18: \( \lambda_3 = 0, \lambda_1 = \lambda_2 = \frac{1}{K} \)
19: else
20: \( \lambda_3 = \frac{1}{K} \)
21: \( \lambda_2 = \frac{1}{K} + 1 \)
22: Compute \( \Omega_{l} \) according to Eq. 6, and compute \( z_{fg}(t), z_{bg}(t) \) per frame \( t \) using Eq. 5a and 5b, resp.
23: Compute global constraint in Eq. 7.
24: Compute label-marginal distributions per query frame prediction \( \{P_l(t)\}_{t=1}^{T} \).
25: end if
26: Compute additional constraints in Eq. 8 and 9.
27: Compute the final loss \( L \) using Eq. 12.
28: Update per frame weights and biases \( \omega^L, b^L \) according to the gradients \( \frac{\partial L}{\partial \omega^L}, \frac{\partial L}{\partial b^L} \).
29: end for
30: return \( \{\omega^L, b^L\} \)
31: end function

We provide an algorithmic summary in pseudocode detailing how the optimization process proceeds with our proposed spatiotemporal regularizers in Algorithm 1. The main
Fig. 3: The main shortcoming in YouTube-VIS is the non-exhaustive labels in the annotations (a-c). An example for exhaustive annotation from MiniVSPW dataset (d). Ground truth is highlighted in red.

Table 1: MiniVSPW vs FS-VOS YouTube-VIS dataset size showing the number of annotated images in training per fold.

| Fold | MiniVSPW | FS-VOS | YouTube-VIS [5] |
|------|----------|--------|-----------------|
| 1    | 157,858  | 15,960 |                 |
| 2    | 153,020  | 20,600 |                 |
| 3    | 71,813   | 20,070 |                 |
| 4    | 158,316  | 20,860 |                 |

Table 2: MiniVSPW dataset statistics. The number of images used during training per fold, along with the number of sampled videos per run during the few-shot inference.

| Fold | Classes | # Images (Train) | # Videos (Inf.) |
|------|---------|-----------------|-----------------|
| 1    | 5       | 157,858         | 610             |
| 2    | 5       | 153,020         | 960             |
| 3    | 5       | 71,813          | 261             |
| 4    | 5       | 158,316         | 640             |

transductive inference technique in the “TTI” function describes the first stage optimization process, which updates the final linear classifier weights and biases. Subsequently, in the second optimization stage (not illustrated in Algorithm 1), this process is followed by keyframe selection to perform additional fine-tuning of the weights learned in the previous stage.

4 FS-VOS Benchmark

The previously proposed FS-VOS protocol on YouTube-VIS [5] has one main shortcoming. YouTube-VIS is not exhaustively labelled, i.e. not all object occurrences in the sequence are labelled; see Figure 3. That limitation can cause issues for both training and few-shot inference, since the evaluation will be skewed to labelled instances only.

In response to this shortcoming, we introduce the MiniVSPW benchmark. This benchmark builds on the VSPW [19] dataset, which is exhaustively and densely labelled. VSPW also provides longer sequences than YouTube-VIS, with a higher annotation frame rate of 15 fps. These attributes make it more challenging and appealing to evaluate few-shot video object segmentation and leverage temporal consistency. Table 1 compares MiniVSPW to YouTube-VIS FS-VOS [5]. VSPW has longer videos with higher annotation rate, which entails a larger number of annotated frames vs YouTube-VIS FS-VOS. Statistics for our benchmark in terms of number of images used for training and episodes (query videos) used in few-shot inference is shown in Table 2.

VSPW is more difficult than YouTube-VIS not only because of its larger size, but also because it has less center bias and fewer salient objects to aid the segmentation vs YouTube-VIS, which has both [13]. Figure 4 (a, b) compares the center bias of both datasets, where center bias is visualized in terms of location of segmentation targets within an image. In particular, we evaluate the center bias for each dataset by calculating the average (normalized to 0-1) groundtruth segmentation masks for each pixel over the entire dataset, cf [13]. It is seen that far more targets in YouTube-VIS appear in the central image region compared to VSPW.

We select a subset of VSPW that has categories overlapping with those of PASCAL-VOC. We specifically focus on PASCAL classes that constitute things classes and ignore stuff classes (i.e., wall, street, etc). We consider stuff classes in our benchmark as background, because it can adversely affect the few-shot segmentation protocol otherwise. During training the established protocol in fewshot segmentation 5 is to label pixels belonging to the novel classes as background. Therefore, if stuff classes are labelled separately from class background during training, they can contaminate the learning process. Our proposed protocol of selecting things classes only will prevent this problem and avoid leaking boundaries of the novel classes during the meta-training stage. An example case of the aforementioned prob-
Table 3: Classes per split (i.e. train, validation and test) for each fold in MiniVSPW benchmark.
Fig. 5: MiniVSPW benchmark demonstrating a case where class “person” is the novel class. During meta-training novel classes are labelled as background as standard in few-shot object segmentation works. From left to right: sample image, segmentation mask when labelling all stuff classes as background and labelling the novel class as background, segmentation mask when keeping the stuff classes and labelling the novel class only as background. This specific example shows the problem with keeping the stuff classes and motivates our choice to label all stuff classes as background to avoid contaminating the learning process with the boundaries of the novel class during the meta-training stage.

since the number of training images in MiniVSPW is ten times that of YouTube-VIS, as shown in Table 1. For all common hyperparameters in both training and inference, we use the same as our baseline [1]. We use stochastic gradient descent with a learning rate of $2.5 \times 10^{-3}$, momentum of 0.9, weight decay of $1 \times 10^{-4}$ and cosine learning rate decay. Label smoothing is used with the smoothing parameter set to 0.1. Random flipping data augmentation also is used. We follow standard few-shot segmentation and few-shot video segmentation practices [26] of assigning the novel class object that exists in training images to background.

During transductive inference our loss weights are initially set to $\lambda_1 = \frac{1}{K}$, $\lambda_2 = \frac{1}{K}$ and $\lambda_3 = 0$, as with our baseline (RePRI [1]). After $L_{\phi}$ iterations, $\lambda_3 = \frac{1}{K}$, with $K$ the number of shots, and $\lambda_2$ is increased by 1, again as with our baseline. These adjustments are made after $L_{\phi}$ iterations, because the algorithms has converged to a better region proportion estimate to begin enforcing temporal coherence.

5.2 Comparison to state of the art

Table 4 provides a comparison of our approach with respect to state-of-the-art FS-VOS alternatives. Both our baseline and proposed approach outperform the recent state-of-the-art meta-learning approach [5], which also uses temporal information, by $1.5 - 2.5\%$ mIoU. This result demonstrates that transductive inference can be sufficient for the few-shot task. Moreover, our approach improves over state-of-the-art single image approaches, the transductive inference baseline by 1% and the meta-learning approach [17] by 3.4%. Still, for fold 4 the transductive inference baseline, [1], outperforms our TTI approach. That particular result arises because fold 4 has some challenging classes that lead to over-segmentation (e.g. “tennis racket”), which is exacerbated through keyframe refinement. Our baseline does not suffer in this way on fold 4, as it does not perform this refinement. In contrast, when video consistency, [14], is considered we outperform our baseline by 5.8%, which demonstrates the consistency of our predictions within a temporal window. Overall, these results demonstrate the value of including temporal modeling in transductive inference.

A simple approach for temporal transductive inference that uses a single set of weights for the novel classes for all frames is reported as “Naive Temporal RePRI”. It sums the losses from our baseline over all frames to update the weights, which degrades the results since the region proportion regularization is conducted with different priors. That flaw motivates our design that keeps separate sets of weights per frame.

We show quantitative results on the 5-shot MiniVSPW benchmark in Table 5. We compare our approach to the strongest state-of-the-art method on YouTube-VIS FS-VOS and what we consider as our single image baseline (RePRI). The results demonstrate that our approach consistently improves with respect to the baseline across both metrics and all folds.

Finally, we compare our run-time for the temporal transductive inference in few-shot video object segmentation to DANet [5] that proposed an online learning scheme that fine-tunes the backbone along with a many-to-many attention comparator. They reported an average run-time of 20 seconds per video on a 2080Ti GPU. We did not have access to the same GPU, but we report results on a lower tier TITAN-X GPU. Our method resulted in a runtime of three seconds per video on Youtube-VIS on average. Thus, our method as it operates only in the final linear classifiers results in an approximate $7 \times$ speedup without fine-tuning the backbone while achieving a considerable gain in mIoU.

5.3 Ablation study

Table 6 shows the gains from our various modules for incorporating temporal information on YouTube-VIS FS-VOS.
Table 4: Comparison to the state of the art on YouTube-VIS with ResNet-50 backbone and five-shot one-way support set. ⋆: approaches that use episodic training. †: approaches that treat the video as a whole. mVC₃ mean video consistency on four folds with temporal window 3. Best and second best methods are highlighted in red and blue, resp.

| Method          | mIoU 1 | mIoU 2 | mIoU 3 | mIoU 4 | Mean 1 | Mean 2 | Mean 3 | Mean 4 | mVC₃ 1 | mVC₃ 2 | mVC₃ 3 | mVC₃ 4 | Mean 1 | Mean 2 | Mean 3 | Mean 4 |
|-----------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| PMMs [38]       | 32.9   | 61.1   | 56.8   | 55.9   | 51.7   | -      | -      | -      | -      | -      | -      | -      | -      | -      | -      |
| PFENet [30]     | 37.8   | 64.4   | 56.3   | 56.4   | 53.7   | -      | -      | -      | -      | -      | -      | -      | -      | -      |
| PPNet [17]      | 45.5   | 63.8   | 60.4   | 58.9   | 57.1   | -      | -      | -      | -      | -      | -      | -      | -      | -      |
| DANet† [5]      | 43.2   | 65.0   | 62.0   | 61.8   | 58.0   | 32.3   | 63.7   | 57.2   | 58.0   | 52.8   | -      | -      | -      | -      |
| RePRI [1]       | 45.8   | 68.6   | 59.3   | 64.2   | 59.5   | 54.1   | 75.6   | 63.9   | 71.6   | 66.3   | -      | -      | -      | -      |
| Naive Temporal RePRI† | 36.6   | 62.0   | 50.2   | 55.2   | 51.0   | 36     | 57.3   | 49.1   | 53.2   | 48.9   | -      | -      | -      | -      |
| TTI† (ours)     | 48.4   | 68.5   | 62.6   | 62.4   | 60.5   | 57.7   | 81.6   | 73.6   | 75.6   | 72.1   | -      | -      | -      | -      |

Table 5: MiniVSPW benchmark reporting results for five-shot one-way support set.

| Method          | mIoU 1 | mIoU 2 | mIoU 3 | mIoU 4 | Mean 1 | mVC₃ 1 | mVC₃ 2 | mVC₃ 3 | mVC₃ 4 |
|-----------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| DANet [5]       | 13.9   | 32.0   | 13.4   | 22.0   | 20.3   | 6.8    | 39.8   | 11.5   | 18.3   |
| RePRI [1]       | 22.7   | 35.9   | 21.6   | 28.3   | 27.1   | 16.9   | 38.4   | 14.6   | 21.6   |
| TTI (Ours)      | 25.3   | 37.1   | 25.1   | 29.6   | 29.3   | 21.2   | 42.9   | 18.7   | 24.9   |

Table 6: Ablations showing mIoU on four folds for two benchmarks. Global Loss: global spatiotemporal regularization, (7). Keyframe Refinement using (13). DCL: dense contrastive learning (10).

![Fig. 6: Video Consistency evaluated with different temporal window for our proposed TTI variants with respect to the single image baseline RePRI. G: video-level global regularizer. K: Keyframe refinement.](image-url)
We report video consistency, $mV C_3\ (13)$, in the ablation, since the focus of our study is improving the temporal consistency of our predictions. It is seen that the global module, $\text{TTI}^{\dagger}$, provides benefit to the mean video consistency, followed by the keyframe refinement, $\text{TTI}^{\ddagger}$. Additionally, we consider improving the feature space via dense contrastive learning (DCL) applied to temporally sampled frames. Again it confirms the benefit of this learning scheme to help improve temporal consistency of the features and consequently the learned linear classifiers for the novel class.

We demonstrate in Figure 6 the video consistency metric for our proposed approach without dense contrastive learning, with and without keyframe fine-tuning with various temporal windows, $w = 3, 5, 7, 9, 11$ in (14), to confirm the consistency of our results. As the temporal window increases the video consistency decreases, since it becomes more challenging to both our baseline and proposed approach (TTI). Interestingly, on the two benchmarks our final approach with spatiotemporal regularization and key frame fine-tuning is consistently improving with respect to the baseline on all four folds. This systematic evaluation on different benchmarks, folds and temporal widows further confirms the added benefit to temporally consistent predictions.

In Table 7, we show our global spatiotemporal regularizer (TTI) and our full method (TTI) results across three metrics on YouTube-VIS. Moreover, we compare to the state-of-the-art FS-VOS method DANet [5] and our single image baseline RePRI [1]. When looking to the ranking score that averages all metrics, mAll, our method outperforms the state of the art with a 2.8% gain. Additionally, it shows the benefit on the three metrics from using our spatiotemporal regularizers with respect to our single image baseline, with the highest gains in the video consistency as expected.

However, note that both our single image baseline RePRI [1] and our method suffer from lower boundary accuracy than DANet [5]. This is mainly due to two reasons: (i) Most importantly, unlike DANet we only operate with the coarsest features extracted from the backbone, while DANet segmentation decoder has skip connections that uses fine resolution (early stage) feature maps. (ii) Use of transductive inference with the region proportion regularization does not entail refined boundaries, which degrades the boundary accuracy as it only uses the label marginal distribution. Nonetheless, we outperform DANet across both mean intersection over union, $mIoU$, mean boundary accuracy, $F$, and mean video consistency with temporal window 3, $mV C_3$ averaged over four folds. Moreover, we report the average of all metrics, mAll, to rank the methods. $\dagger$ indicates the global spatiotemporal regularizer only, $\ddagger$ indicates our full method. Best and second best methods are highlighted in red and blue, resp.
outweighs the cases where the opposite is seen. This result indicates a notable gain with respect to the baseline that consistently improves with the increasing number of support set examples. The plot shows that our approach has a higher K-shot stability score compared to the baseline.

We are the first to quantify and show its impact as an overfitting analysis for few-shot approaches. Figure 7(a) shows that support set examples in the support set confuse the model rather than improve it. We are not the first to show that support set examples can affect the few-shot models differently \[41\]; however, we are the first to quantify and show its impact as an analysis for few-shot approaches. Figure 7(a) shows that sequences suffering from this phenomenon decrease with our approach, while our spatiotemporal regularizer succeeds.

We also show the miou gain or reduction from our approach with respect to the baseline as a function of K-shot stability in Figure 7(b). The plot shows that our approach has a notable gain with respect to the baseline that consistently outweighs the cases where the opposite is seen. This result shows our temporal regularizer reducing failures in these overfitting scenarios over our baseline that does not take temporal constraints into account. Additionally, Figure 7(d, e) shows qualitative examples of overfitting, with (d) providing predictions using the five-shot support set and (e) showing predictions from one-shot support set standalone. It is seen that examples where the support set is poorly representative of the query lead to overfitting and correspondingly bad predictions.

5.4 Overfitting analysis

All experiments in this section are conducted without keyframe selection or contrastive loss. We make this choice to focus analysis on the effect of learning a separate linear classifier per frame followed by spatiotemporal regularization vs not using temporal regularization, as is the case in the single image baseline RePRI \[1\]. Overfitting is expected when learning the linear classifies on few-shot labelled support sets, as it can lead to degenerate solutions. Our baseline includes regularization on a single frame to help overcome some of these issues, but that approach is sensitive to a prior on foreground/background region proportion \[1\]. A diagnostic of one form of overfitting is the accuracy for a five-shot \( (K = 5) \) support set, \( S = \{ X^k_s, M^k_s \}_{k=1}^K \), being worse than the maximum accuracy obtained from using standalone examples, \( (X^k_s, M^k_s) \), from that set in a one-shot setting. This pattern indicates that certain examples in the support set confuse the model and negatively impact the query segmentation.

Let accuracy for five-shot and maximum accuracy across standalone examples be \( \text{IoU}_5 \) and \( \max_k (\text{IoU}_5^k) \), resp. We calculate the K-shot stability score as, \( \max_k (\text{IoU}_5^k) = \text{IoU}_5 \); results are shown in Figure 7. Typically, accuracy should improve with increased shot size, but in certain cases it can lead to the opposite, as shown for our baseline in Figure 7(a). While the majority of sequences benefit from additional support set examples, certain overfitting cases occur, where examples in the support set confuse the model rather than improve it. We are not the first to show that support set examples can affect the few-shot models differently \[41\]; however, we are the first to quantify and show its impact as an analysis for few-shot approaches. Figure 7(a) shows that sequences suffering from this phenomenon decrease with our temporal regularizer compared to the baseline.

We show in examples three and four of the video that our spatiotemporal regularizer when used during optimization reduces the effect of overfitting on the support set.
set, unlike the baseline, RePRI. These results provide further support of those reported quantitatively in Figure 6. In particular, TTI avoids degenerate solutions that can occur due to early overfitting and erroneous prior label-marginal distribution, $P_x$. In example five we show a case where RePRI outperforms TTI. That example shows a challenging scenario, for the class “tennis racket”, where both our method and the baseline face difficulty in segmentation. It is seen that our spatiotemporal regularizers can lead to oversegmentation in certain frames. Nonetheless, we have demonstrated in Section 5.4 that over all the different folds we provide more gain and avoid multiple overfitting scenarios where our baseline suffers in comparison.

6 Ethics and broader impact statement

Few-shot video object segmentation, where the query set to be segmented is a video, is a crucial task that can help reduce the annotation cost required to label large-scale video datasets. It can serve a variety of applications in autonomous systems and medical image processing which require the model to learn from few labelled examples for novel classes that are beyond the closed set of training classes with abundant labels. It can also help bridge the gap between developing and developed countries, where the former lacks the resources necessary to annotate large-scale labelled datasets that are required in a variety of tasks that serves the community such as, the use of satellite imagery in agricultural monitoring and crop management. We believe our work in general provides positive impact in empowering developing countries to establish labelled datasets that satisfy the needs of their own communities rather than following public benchmarks.

However, as with many artificial intelligence algorithms, video object segmentation can have negative societal impacts, e.g., through application to automatic target detection in military and surveillance systems. There are emerging movements to limit such applications, e.g., pledges on the part of researchers to ban use of artificial intelligence in weaponry systems. We have participated in signing that pledges on the 5.4 that over all the different folds we provide more gain and avoid multiple overfitting scenarios where our baseline suffers in comparison.

7 Data availability

All the datasets used in this study are linked through our repository at https://github.com/MSiam/tti_f

8 Conclusion

We have presented a novel temporal transductive inference approach that uses a global constraint to improve the accuracy of FS-VOS. This constraint is enforced as a loss during learning to address weight consistency across a video. This operation is followed by keyframe fine-tuning to improve the final learned classifiers in a transductive manner. Our approach outperforms state-of-the-art alternatives on a standard benchmark. We also introduced the MiniVSPW benchmark to address the problem with non-exhaustive annotations provided in YouTube-VIS by providing annotations that label all occurrences of each novel semantic category. Our approach also shows state-of-the-art performance on this new benchmark when compared to the strongest alternative.

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