

# Space-Time Correspondence as a Contrastive Random Walk

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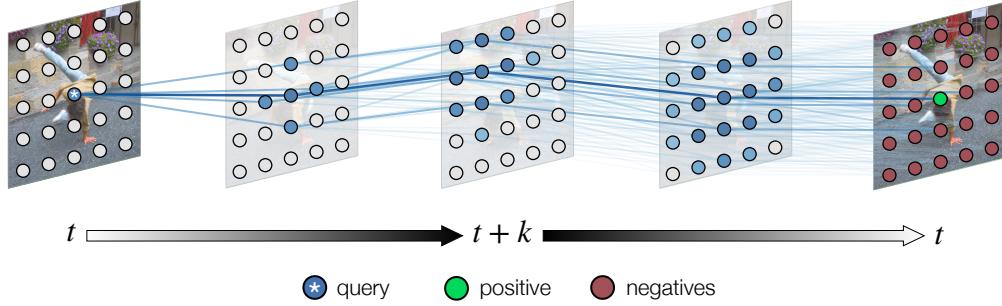


Figure 1: We represent video as a graph, where nodes are image patches, and edges are affinities (in some feature space) between nodes of neighboring frames. Our aim is to learn features such that temporal correspondences are represented by strong edges. We learn to find paths through the graph by performing a random walk between query and target nodes. A contrastive loss encourages paths that reach the target, implicitly supervising latent correspondence along the path. Learning proceeds *without labels* by training on a *palindrome* sequence, walking from frame  $t$  to  $t + k$ , then back to  $t$ , using the initial node itself as the target. Please see our [webpage](#) for videos.

## Abstract

This paper proposes a simple self-supervised approach for learning representations for visual correspondence from raw video. We cast correspondence as link prediction in a space-time graph constructed from a video. In this graph, the nodes are patches sampled from each frame, and nodes adjacent in time can share a directed edge. We learn a node embedding in which pairwise similarity defines transition probabilities of a random walk. Prediction of long-range correspondence is efficiently computed as a walk along this graph. The embedding learns to guide the walk by placing high probability along paths of correspondence. Targets are formed without supervision, by cycle-consistency: we train the embedding to maximize the likelihood of returning to the initial node when walking along a graph constructed from a palindrome of frames. We demonstrate that the approach allows for learning representations from large unlabeled video. Despite its simplicity, the method outperforms the self-supervised state-of-the-art on a variety of label propagation tasks involving objects, semantic parts, and pose. Moreover, we show that self-supervised adaptation at test-time and edge dropout improve transfer for object-level correspondence.

## 1 Introduction

There has been a flurry of advances in self-supervised representation learning from still images, yet this has not translated into commensurate advances in learning from *video*. In the early days of computer vision, video was thought to be a simple extension of an image into time, to be modeled

by a spatio-temporal  $XYT$  volume [57, 95]. This view is now seeing a resurgence in the form of 3D convolutions [11], often used for tasks like action recognition. Yet, treating time as just another dimension is limiting [21]. One practical issue is the sampling rate mismatch between  $X$  and  $Y$  vs.  $T$ . But a more fundamental problem is that a physical point depicted at position  $(x, y)$  in frame  $t$  might not have any relation to what we find at that same  $(x, y)$  in frame  $t + k$ , as the object or the camera will have moved in arbitrary (albeit smooth) ways. This is why the notion of *temporal correspondence* — “what went where” [91] in a video — is so fundamental for learning from temporal visual data.

Recent self-supervision methods, such as those based on triplet losses and contrastive learning [80, 70, 92, 77, 31, 13], are effective for learning similarity between inputs when matching views (correspondences) are assumed to be known, e.g. formed by data augmentation. Temporal correspondences in video, however, are *latent*, and learning to find them leads to a chicken-and-egg problem: we need correspondences to train our model, yet we rely on our model to find these correspondences in the first place. An emerging line of work aims to address this problem by “bootstrapping” from an initially random representation, inferring which correspondences should be learned in a self-supervised manner e.g. via cycle-consistency of time [88, 84, 44]. While this is a promising direction, current methods rely on complex and greedy tracking procedures that may be susceptible to local optima, especially when applied recurrently in time.

In this paper, we learn a representation for temporal correspondence by formulating the problem as probabilistic pathfinding on a graph. The graph is constructed from a video, where nodes are image patches and only nodes in neighboring frames share an edge. The strength of the edge is determined by a learned similarity function, whose aim is to place large weight along paths linking visually corresponding patches (see Figure 1). Inspired by Meila and Shi [53], we capture global connectivity in the graph by modeling local transition probabilities of a random walker stepping through time. Our learning problem requires supervision — namely, the target that the walker should aim for. In lieu of ground truth labels, we use the idea of cycle-consistency [99, 88, 84], by turning training videos into *palindromes*, where the first half is repeated backwards. This provides every path with a target — getting back to its starting point. With this formulation, we can view each step of the random walker as a contrastive learning problem [60], where the walker’s target provides supervision for the entire chain of intermediate steps.

The central benefit of the proposed model is that it efficiently considers many possible paths through the graph by simply computing the expected outcome of a random walk. This allows the model to obtain a useful learning signal from all patches in the video simultaneously, and overcome ambiguity to learn from harder examples encountered during training. Despite its simplicity, the method learns a representation that is effective for a variety of correspondence tasks, without any additional adaptation. We obtain results that outperform state-of-the-art self-supervised methods on video object segmentation, pose keypoint propagation, and semantic part propagation. The model scales effectively, obtaining improvements in performance as the length of the random walks used for training increases. We also show several extensions of the model that further improve the quality of its correspondences for object segmentation, including test-time adaptation, and an edge dropout [73] technique that encourages the model to group “common-fate” [90] nodes together.

## 2 Contrastive Random Walks on Video

We represent each video as a directed graph where nodes are patches, and weighted edges connect nodes in neighboring frames. Let  $\mathbf{I}$  be a set of frames of a video and  $\mathbf{q}_t$  be the set of  $N$  nodes extracted from frame  $\mathbf{I}_t$ , e.g. by sampling overlapping patches in a grid. An encoder  $\phi$  maps nodes to  $l_2$ -normalized  $d$ -dimensional vectors, which we use to compute a pairwise similarity function  $d_\phi(q_1, q_2) = \langle \phi(q_1), \phi(q_2) \rangle$  and an embedding matrix for  $\mathbf{q}_t$  denoted  $Q_t \in \mathbb{R}^{N \times d}$ . We convert pairwise similarities into non-negative affinities by applying a softmax (with temperature  $\tau$ ) over edges departing from the node. For two adjacent timesteps  $t$  and  $t + 1$ , the stochastic matrix of affinities is

$$A_t^{t+1}(i, j) = \text{softmax}(Q_t Q_{t+1}^\top)_{ij} = \frac{\exp(d_\phi(\mathbf{q}_t^i, \mathbf{q}_{t+1}^j)/\tau)}{\sum_l \exp(d_\phi(\mathbf{q}_t^i, \mathbf{q}_{t+1}^l)/\tau)}, \quad (1)$$

where the softmax is row-wise. Note that this describes only the *local* affinity between the patches of two video frames,  $\mathbf{q}_t$  and  $\mathbf{q}_{t+1}$ . The affinity matrix for the entire graph, which relates all nodes in the video as a Markov chain, is sparse and composed of local affinity matrices.

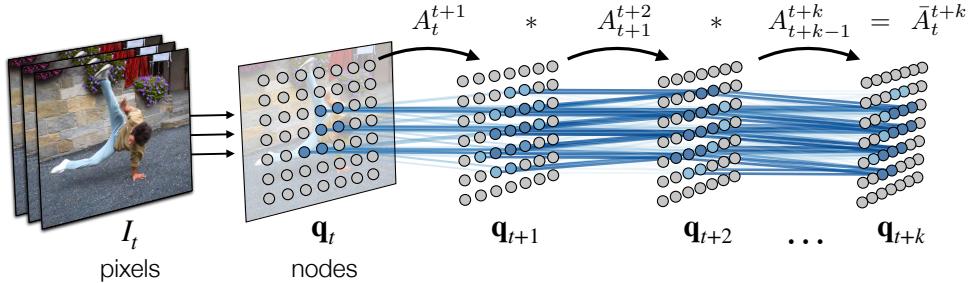


Figure 2: **Correspondence as a Random Walk.** We build a space-time graph by extracting nodes from each frame and allowing directed edges between nodes in neighbouring frames. The transition probabilities of a random walk along this graph are determined by learned pairwise node similarity.

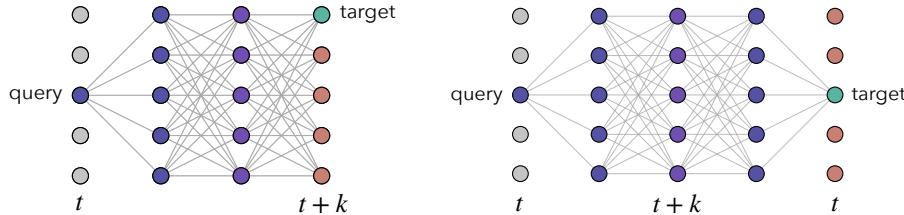


Figure 3: **Learning to Walk on Video.** (a) Specifying a target multiple steps in the future provides implicit supervision for *latent* correspondences along each path (*left*). (b) We can construct targets for free by choosing palindromes as sequences for learning (*right*).

Given the spatio-temporal connectivity of the graph, a step of a random walker on this graph can be seen as performing probabilistic tracking by *contrasting* similarity of neighboring nodes (using  $\phi$ ). Let  $X_t$  be the state of the walker at time  $t$ , with transition probabilities  $A_t^{t+1}(i, j) = P(X_{t+1} = j | X_t = i)$ , where  $P(X_t = i)$  is the probability of being at node  $i$  at time  $t$ . With this view, we can formulate long-range correspondence as walking multiple steps along the graph (Figure 2). We chain the transitions to obtain the distribution over nodes after  $k$  steps:

$$\bar{A}_t^{t+k} = \prod_{i=0}^{k-1} A_{t+i}^{t+i+1} = P(X_{t+k} | X_t). \quad (2)$$

**Guiding the walk.** Our aim is to train the embedding to encourage the random walker to follow paths of corresponding patches as it steps through time. While ultimately we will train without labels, for motivation suppose that we did have ground-truth correspondence labels between nodes in two frames of a video,  $t$  and  $t + k$  (Figure 3a). We could use these labels to fit the embedding by maximizing the probability that a random walk beginning at a *query* node at  $t$  ends at the *target* node at time  $t + k$ :

$$\mathcal{L}_{sup} = \mathcal{L}_{CE}(\bar{A}_t^{t+k}, Y_t^{t+k}) = - \sum_{i=1}^N \log P(X_{t+k} = Y_t^{t+k}(i) | X_t = i), \quad (3)$$

where  $\mathcal{L}_{CE}$  is cross entropy loss and  $Y_t^{t+k}$  are correspondence labels for matching time  $t$  to  $t + k$ . Under this formulation, the walk can be viewed as a chain of contrastive learning problems. Providing supervision at *every* step amounts to maximizing similarity between the embeddings of query and target nodes adjacent in time, while minimizing similarity to embeddings of all other neighbors.

The more interesting case is supervision of long-range correspondence, i.e. when  $k > 1$ . In this case, the labels of  $t$  and  $t + k$  provide *implicit* supervision for intermediate frames  $t + 1, \dots, t + k - 1$ , assuming that latent correspondences exist to link  $t$  and  $t + k$ . Recall that in computing  $P(X_{t+k} | X_t)$ , we marginalize over all intermediate paths that link nodes in  $t$  and  $t + k$ . By minimizing  $\mathcal{L}_{sup}$ , we shift weight to paths that link the query and target. In relatively easy cases (e.g. smooth videos with no occlusions) the paths that the walker takes from each node will not overlap, and these paths will simply be reinforced. In harder cases, such as where deformation or multi-modality make correspondence ambiguous, the transitions will be split over multiple latent correspondences, such

that we consider a distribution over paths. The embedding captures similarity between nodes in a manner that allows for hedging probability over paths to overcome ambiguity, while avoiding transitions to nodes that lead the walker astray.

**Self-supervision with palindromes.** How can we identify query-target pairs that are known to correspond, without human supervision? We can consider training on graphs in which correspondence between the first and last frames are known, by construction. One such class of sequences are *palindromes*, i.e. sequences that are unchanged when reversed, for which correspondence is known since the first and last frames are identical. Given a sequence of frames  $(I_t, \dots, I_{t+k})$ , we form the palindrome by simply concatenating the sequence with a temporally reversed version of itself:  $(I_t, \dots, I_{t+k}, \dots, I_t)$ . Treating each query node’s position as its own target (Figure 3b), we obtain the following cycle-consistency objective, where the ground truth labels,  $I$ , are the identity matrix:

$$\mathcal{L}_{cyc}^k = \mathcal{L}_{CE}(\bar{A}_t^{t+k} \bar{A}_{t+k}^t, I) = - \sum_{i=1}^N \log P(X_{t+2k} = i | X_t = i) \quad (4)$$

This self-supervised formulation enables learning correspondences over multiple frames from raw video. The model computes a distribution over soft matches at every time step, allowing backpropagation over all paths through the graph during training. This allows the model to consider long-range correspondences, and also to consider and eventually learn possible matches that are dissimilar in local appearance but nonetheless may correspond.

**Contrastive learning with latent views.** To help explain why this model learns a useful representation, we can interpret it as contrastive learning with latent views. A standard contrastive learning formulation brings two views of the same example together by learning a representation that minimizes the loss  $\mathcal{L}_{CE}(U_1^2, I)$  [60], where  $U_1^2 \in \mathbb{R}^{n \times n}$  is the matrix of pairwise dot products between the vectors of the first and second views of  $n$  examples, converted into a stochastic matrix by softmax as in Equation 1. Suppose, however, that we do not know *which* views should be matched with one another — merely that there should be a soft one-to-one correspondence between them. This can be formulated as contrastive learning guided by a cycle-consistency constraint: each image chooses from among the possible distractors, composing  $U_1^2$  with the “transposed” stochastic matrix  $U_2^1$  of similarities between the second and first view. This produces the loss  $\mathcal{L}_{contrast} = \mathcal{L}_{CE}(U_1^2 U_2^1, I)$ , which is akin to the cycle walk loss of Equation 4. In this work, we chain contrastive predictions between latent views to form a cycle of multiple steps in the embedding space, which makes for a more challenging self-supervision task due to compounding error.

## 2.1 Edge Dropout

Beyond correspondences of image patches, one could also consider correspondence on the level of broader *segments*, where points within a segment have strong affinity to all other points in the segment. This inspires a trivial extension of our method—randomly dropping edges from the graph, thereby forcing the walker to consider alternative paths. We apply dropout [73] (with rate  $\delta$ ) to the transition matrix  $A$  to obtain  $\tilde{A} = \text{dropout}(A, \delta)$  and then renormalize. The resulting transition matrix  $B$  and noisy cycle loss are:

$$B_{ij} = \frac{\tilde{A}_{ij}}{\sum_l \tilde{A}_{il}} \quad \mathcal{L}_{cyc}^k = \mathcal{L}_{CE}(B_{t+k}^t B_t^{t+k}, I). \quad (5)$$

Edge dropout affects the task by randomly obstructing paths, thus encouraging hedging of mass to paths highly correlated with the ideal path, similar to the effect in spectral-based segmentation [72, 53]. We will see in Section 3.2 that edge dropout improves transfer to object-level correspondence tasks.

## 2.2 Implementation

We now describe in detail how we construct the graph, and how we parameterize the node embedding  $\phi$ . Algorithm 1 provides complete pseudocode for the method.

**Pixels to Nodes.** At training time, we follow [34], where patches of size  $64 \times 64$  are sampled on a  $7 \times 7$  grid from a  $256 \times 256$  image (i.e. 49 nodes per frame). Patches are spatially jittered to prevent matching based on borders. At test time, we found that we could reuse the convolutional feature map between patches instead of processing the patches independently [46], making the features computable with only a single feed-forward pass of our network.<sup>1</sup>

<sup>1</sup>Despite our best efforts, we found that using a single convolutional feature map at training left the learning algorithm susceptible to learning shortcut solutions. We provide more details in Section B.



Figure 4: Qualitative results for label propagation under our model for object, pose, and semantic part propagation tasks. The first frame is indicate with a blue outline. **Please see our [webpage](#) for video results**, as well as a qualitative comparison with other methods.

**Encoder  $\phi$ .** We create an embedding for each image patch using a convolutional network, namely ResNet-18 [33]. Following common practice in similarity learning [31], we apply a linear projection and  $l_2$  normalization after the average pooling layer, obtaining a 128-dimensional vector.

**Subcycles.** During training, we consider cycles of multiple lengths. For a sequence of length  $T$ , we optimize all subcycles:  $\mathcal{L}_{train} = \sum_{i=1}^T \mathcal{L}_{cyc}^i$ . This loss encourages the sequence of nodes visited in the walk to be a palindrome, i.e. on a walk of length  $N$ , the node visited at step  $t$  should be the same node as  $N - t$ . It also leads to a natural training curriculum, as short walks are easier to learn than long ones. These additional losses can be computed efficiently, since they share the same affinity matrices (Equation 1).

**Training.** We train  $\phi$  using the (unlabeled) videos from Kinetics [11], with Algorithm 1. We used the Adam optimizer [39] for one million updates, with 24 sequences per batch and a learning rate of  $10^{-4}$ . We use a temperature of  $\tau = 0.07$  in Equation 1, following [92] and resize frames to  $256 \times 256$  (before extracting nodes as above). Except when indicated otherwise, we set edge dropout to 0. While we trained the model with 24-sequence batches split over three 1080Ti GPUs, we were able to train the model on a single GPU (with batch size 8).

### 3 Experiments

We demonstrate that the learned representation is effective for dense label propagation tasks, ablate the effects of edge dropout and training sequence length, and evaluate self-supervised adaptation at test-time. Please find additional comparisons to supervised methods, ablations and qualitative results in the Appendix.

#### 3.1 Transferring the Learned Representation

We apply the trained embedding on label propagation tasks involving objects, semantic parts, and human pose. To isolate the effect of the representation, we use a simple algorithm for inference. Qualitative results are shown in Figure 4.

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#### Algorithm 1 Pseudocode in a PyTorch-like style.

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```

# load a minibatch x with B sequences
for x in loader:
    # Split image into patches
    # B x C x T x H x W -> B x C x T x P x h x w
    x = unfold(x, (patch_size, patch_size))
    x = spatial_jitter(x)
    # Embed patches (B x C x T x P)
    v = 12_norm(resnet(x))

    # Transitions from t to t+1 (B x T x P x P)
    A = bmm(v[:, :, :-1], v[:, :, 1:]) / temperature

    # Transition similarities for palindrome graph
    AA = cat((A, A[:, :, ::-1].transpose(-1, -2)), 1)

    # Walk
    At = eye(P)
    for t in range(2*T):
        At = bmm(softmax(dropedge(AA[:, t]), dim=-1), At)

    # Target is the original node (Equation 4)
    loss = cross_ent_loss(At, labels=[range(P)]*B)
    loss.backward()

```

---

bmm: batch matrix multiplication; eye: identity matrix; cat: concatenation.

Method	Resolution	Train Data	$\mathcal{J} \& \mathcal{F}_m$	$\mathcal{J}_m$	$\mathcal{J}_r$	$\mathcal{F}_m$	$\mathcal{F}_r$
ImageNet [33]	1×	ImageNet	62.1	59.8	68.3	64.4	72.4
MoCo [31]	1×	ImageNet	60.1	57.1	66.0	63.1	71.9
VINCE [25]	1×	Kinetics	60.4	57.9	66.2	62.8	71.5
CorrFlow [43]	2×	OxUvA	50.3	48.4	53.2	52.2	56.0
MAST [42]	2×	OxUvA	63.7	61.2	73.2	66.3	78.3
MAST [42]	2×	YT-VOS	65.5	63.3	73.2	67.6	77.7
Colorization [83]	1×	Kinetics	34.0	34.6	34.1	32.7	26.8
TimeCycle [88]	1×	VLOG	48.7	46.4	50.0	50.0	48.0
UVC [44]	1×	Kinetics	58.1	56.8	65.7	59.5	65.1
UVC+track [44]	1×	Kinetics	59.5	57.7	68.3	61.3	69.8
<b>Ours</b>	1×	Kinetics	<b>66.1</b>	<b>63.8</b>	<b>74.9</b>	<b>68.7</b>	<b>80.9</b>
w/ dropout	1×	Kinetics	67.6	64.8	76.1	70.2	82.1
w/ dropout & test-time training	1×	Kinetics	68.3	65.5	78.6	71.0	82.9

Table 1: **Video object segmentation results on DAVIS 2017 val set** Comparison of our method (3 variants), with previous self-supervised approaches and strong image representation baselines. *Resolution* indicates if the approach uses a high-resolution (2x) feature map. *Train Data* indicates which dataset was used for pre-training.  $\mathcal{F}$  is a boundary alignment metric, while  $\mathcal{J}$  measures region similarity as IOU between masks. Comparison to supervised methods can be found in Section A.

**Label Propagation.** All evaluation tasks considered can be cast as video label propagation, where the task is to predict labels for each pixel in *target* frames of a video given only ground-truth for the first frame (i.e. the *source*). We use the model as a similarity function for prediction by  $k$ -nearest neighbors, which is natural under our model and follows prior work for fair comparison [88, 44]. Say we are given source nodes  $\mathbf{q}_s$  with labels  $L_s \in \mathbb{R}^{N \times C}$ , and target nodes  $\mathbf{q}_t$ . Let  $K_t^s$  be the matrix of transitions between  $\mathbf{q}_t$  and  $\mathbf{q}_s$  (Equation 1), with the special property that only the top- $k$  transitions are considered per source node. Then, labels  $L_t$  are propagated as  $L_t = K_t^s L_s$  where each row corresponds to the soft distribution over labels for a node, predicted by  $k$ -nearest neighbor under  $d_\phi$ . Following common practice [88, 43, 44], we use a queue of context frames and restrict the set of source nodes considered to be within a spatial neighborhood of the query node for efficiency. The source set includes nodes of the first labeled frame, as well as the nodes in previous  $m$  frames, whose predicted labels are used for auto-regressive propagation.

**Baselines.** We compare to a variety of methods, all of which use ResNet-18 [32] as the network backbone. First, we consider strong image- and video-based representation learning methods. Following the setup in [88] and for consistency across methods (including our own), we use the features in the last convolutional feature map as node embeddings at test-time. We consider a strong supervised training method, a model trained on **ImageNet** [16]. We also consider a strong self-supervised method, **MoCo** [31], due to state-of-the-art performance, code availability, efficiency of training. Finally, we compare with the video-based contrastive learning method, **VINCE** [25], which extends MoCo to videos (Kinetics) with views from data augmentation *and* neighbors in time.

We also compare with state-of-the-art self-supervised temporal correspondence approaches. **Wang et al.** [88] uses cycle-consistency to train a spatial transformer as a deterministic patch tracker. We also consider methods based on the **Colorization** approach of Vondrick et al. [83], including high-resolution methods: **CorrFlow** [43] and **MAST** [42]. CorrFlow combines cycle consistency with colorization. MAST uses a deterministic region localizer and memory bank for high-resolution colorization, and performs multi-stage training on [79]. Notably, both methods use feature maps that are significantly higher resolution than other approaches (2×), which they implement by removing the initial pooling layer of ResNet. Finally, **UVC** [44] jointly optimizes losses for colorization, grouping, pixel-wise cycle-consistency, and patch tracking with a deterministic patch localizer.

### 3.1.1 Video Object Segmentation

We evaluate our model on DAVIS 2017 [67], a popular benchmark for video object segmentation. We consider the semi-supervised setting, which involves multi-object (i.e. 2-4) label propagation. Following common practice, we evaluate on 480p resolution images and use  $k = 5, m = 8$ . We report mean (m) and recall (r) of standard boundary alignment ( $\mathcal{F}$ ) and region similarity ( $\mathcal{J}$ ) metrics, detailed in [64].

As shown in Table 1, our approach outperforms all other self-supervised methods, without relying on machinery such as localization modules or multi-stage training. Our method gives a relative improvement of 15% compared to state-of-the-art methods that train on Kinetics. We also outperform [42] despite being more simple at train and test time, and using a lower-resolution feature map. Moreover, we perform better than state-of-the-art image-level self-supervised learning approaches MoCo [31] and VINCE [25], suggesting that for tasks that involve dense similarity, it may not be optimal to choose views for contrastive learning by random crop data augmentation of neighboring frames. Finally, we perform competitively with many of the supervised methods with architectures specially designed for dense tracking [64, 10, 85]; details can be found in Section A.

### 3.1.2 Pose Tracking

We consider pose tracking on the JHMDB benchmark, which involves tracking 15 keypoints. We follow the evaluation protocol of [44], using  $320 \times 320$ px images and  $m = 7$  frames of context. As seen in Table 2, our model outperforms the self-supervised state-of-the-art, including video colorization models that directly optimize for fine-grained matching with pixel-level objectives [44]. We attribute this success to the fact that our model sees sufficient hard negative samples drawn from the same image at training time to learn discriminative correspondence.

### 3.1.3 Video Part Segmentation

We consider the semantic part segmentation task of the Video Instance Parsing (VIP) benchmark [98], which involves propagating labels of 20 parts — such as arm, leg, hair, shirt, hand — requiring more precise correspondence than DAVIS. The sequences are longer and sampled at a lower frame rate. We follow the evaluation protocol of [44], using  $560 \times 560$ px images and  $m = 1$ . We outperform the self-supervised state-of-the-art, and when using more temporal context (i.e.  $m = 4$ ), we outperform the benchmark’s supervised approach [98].

## 3.2 Variations of the Model

**Edge dropout.** We test the hypothesis (Figure 5b) that edge dropout should improve performance on the object segmentation task, by training our model with different edge dropout rates: {0, 0.1, 0.2, 0.3, 0.4}. We find that small amounts of dropout provide a significant improvement on the downstream DAVIS benchmark. We hypothesize that edge dropout simulates occasional partial occlusion, forcing the network to form alternate matches if necessary.

**Path length.** We also asked how important it is for the model to perform its random walk over long temporal distances during training, by using clips of length 2, 4, 6, or 10 (resulting in paths of length 4, 8, 12, or 20). Longer sequences make for harder tasks due to compounding error. We found that longer training sequences results in accelerated convergence as well as improved performance on the DAVIS task (Figure 5c). This is in contrast to prior work [88]; we attribute this success to considering multiple paths at training time, which allows for tracking along and thus learning from long sequences, despite ambiguity.

**Performance as function of training time** We found that the model’s downstream performance on DAVIS improves as more data is seen during self-supervised training (Figure 5a). In contrast to Wang et al [88], there is no evidence of saturation of performance on the downstream task.

## 3.3 Test-time Training

A key benefit of self-supervised learning is that, because there is no reliance on labeled data, training need not be limited to the training phase, but can continue during deployment [3, 56, 75]. Our approach is especially suited for such adaptation, given the non-parametric inference procedure. We ask whether the model can improve its ability to find object correspondences by fine-tuning the embedding *at test time* on a novel video. Given an input video, we can perform a small number of iterations of gradient descent on the self-supervised loss (Algorithm 1) *prior* to label propagation.

Method	mIoU	Parts		Pose	
		PCK@0.1	PCK@0.2	PCK@0.1	PCK@0.2
TimeCycle [88]	28.9	57.3	78.1		
UVC [44]	34.1	58.6	79.6		
Ours	36.0	59.0	83.2		
Ours + context	<b>38.6</b>	<b>59.3</b>	<b>84.9</b>		
ResNet-18 [32]	31.9	53.8	74.6		
ATEN [98]	<b>37.9</b>	—	—		
Yang et al. [93]	—	<b>68.7</b>	<b>92.1</b>		

Table 2: **Part and Pose Propagation tasks**, with the VIP and JHMDB benchmarks, respectively. For comparison, we show supervised methods below.

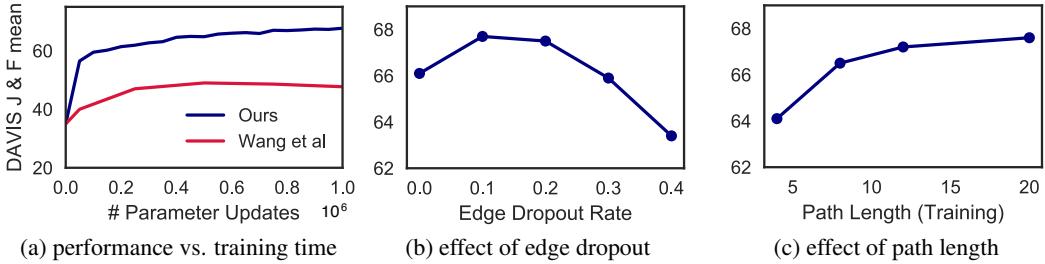


Figure 5: **Variations of the Model.** (a) Downstream task performance as a function of training time. (b) Moderate edge dropout improves object-level correspondences. (c) Training on longer paths is beneficial. All evaluations are on the DAVIS segmentation task.

We argue it is most natural to consider an online setting, where the video is ingested as a stream and fine-tuning is performed continuously on the sliding window of  $k$  frames around the current frame. Note that only the raw, unlabeled video is used for this adaptation; we do not use the provided label mask. As seen in Table 1, test-time training gives an improvement on the video object segmentation task. Interestingly, we see most improvement (+2.5%) in the recall of the region similarity metric  $\mathcal{I}_{recall}$  (which measures how often more than 50% of the object is segmented). More experiment details can be found in Section E.

## 4 Related Work

**Temporal Correspondence.** Many early methods represented video as a spatio-temporal  $XYT$  volume, where patterns, such as lines or statistics of spatio-temporal gradients, were computed for tasks like gait tracking [57] and action recognition [95]. Because the camera was usually static, this provided an implicit temporal correspondence via  $(x, y)$  coordinates. For more complex videos, optical flow [48] was used to obtain short-range explicit correspondences between patches of neighboring frames. However, optical flow proved too noisy to provide long-range composite correspondences across many frames. Object tracking was meant to offer robust long-range correspondences for a given tracked object. But after many years of effort (see [22] for overview), that goal was largely abandoned as too difficult, giving rise to “tracking as repeated detection” paradigm [68], where trained object detectors are applied to each frame independently. In the case of multiple objects, the process of “data association” connects these detections into coherent object tracks. Data association is often cast as an optimization problem for finding paths through video that fulfill certain constraints, e.g. appearance, position overlap, etc. This can be addressed in a variety of ways, including dynamic programming, particle filtering, various graph-based combinatorial optimization, and more recently, graph neural networks [96, 69, 6, 66, 12, 94, 38, 37, 40, 9]. Our work can be thought of as performing soft, contrastive data association directly on pixels, as a means for representation learning.

**Graph Partitioning and Graph Representation Learning.** Graphs have also been widely used in image and video segmentation. Given a video, a graph would be formed by connecting pixels in spatio-temporal neighborhoods, followed by spectral clustering [71, 72, 23] or MRF/GraphCuts [8]. Most relevant to us is work of Meila and Shi [53], which posed Normalized Cuts as a Markov random walk, describing an algorithm for learning an affinity function by fitting the transition probabilities to be uniform within segments and zero otherwise. While above methods solve for connectivity given fixed nodes, graph representation learning approaches solve for node representations given fixed connectivity [29]. Most related, similarity learning approaches define neighborhoods of positives with fixed (i.e.  $k$ -hop neighborhood) or stochastic (i.e. random walk) heuristics [65, 27, 76], while sampling negatives at random. Backstrom et al. [4] learns to predict links by supervising a random walk on social network data. Likewise, we learn to predict links between patches in a video, but do so to learn a representation and supervise the walker with cycle-consistency.

**Visual Representation with Self-Supervision.** Most work in self-supervised representation learning can be interpreted as data imputation: given an example, the task is to predict a part — or *view* — of its data given another view [5, 15, 14]. Earlier work leveraged unlabeled visual datasets by constructing *pretext* prediction tasks [17, 58, 97]. For video, temporal information makes for natural pretext tasks, including future prediction [26, 74, 52, 47, 50], arrow of time [55, 89], motion estimation [1, 36, 78, 45] or audio [62, 2, 61, 41]. The use of off-the-shelf tracking to provide supervisory signal for learning visual similarity has also been explored [86, 87, 63]. Recent progress

in self-supervised learning has focused on improving techniques for large-scale distance learning, e.g. by combining the cross-entropy loss with negative sampling [28, 54]. Sets of views are formed by composing various data augmentations of the same instance [18, 7, 92], with domain knowledge being crucial for picking the right data augmentations. Strong image-level visual representations can be learned by heuristically choosing views that are close in space [80, 31, 13], in time [70, 30, 25] or both [35, 77], even when relying on noisy negative samples. However, forcing neighboring frames or crops to be similar is not always desirable because they may not be in correspondence. In contrast, we adaptively choose which pairs of crops to bring closer, which amounts to a sort of automatic view selection.

**Self-supervised Correspondence and Cycle-consistency in Time** Our approach is directly inspired by recent work that uses cycle-consistency [99, 19] in time as supervisory signal for learning visual representations from video [88, 84]. The key idea is to use self-supervised tracking as a pretext task: given a patch, first track forward in time, then backward, with the aim of ending up where it started, forming a cycle. At training, these methods rely on deterministic trackers in a greedy manner, which limits them to sampling, and learning from, one path at a time. In contrast, our approach maintains a distribution over matches at every time step, allowing us to assign credit over many paths to obtain a dense learning signal and overcome ambiguity. Li et al. [44] considers only pairs of frames, combining patch tracking with other losses including color label propagation [83], spatial concentration, and cycle-consistency via an orthogonality constraint [24]. Recently, Lai et al. [43, 42], inspired by [83], explore and improve architectural design decisions that yield impressive results on video object segmentation and tracking tasks. While colorization is a useful cue, the underlying assumption that corresponding pixels have the same color is often violated, e.g. due to changes in lighting or deformation. In contrast, our loss permits correspondences between image regions that may have significant differences in their appearance.

## 5 Discussion

We presented a simple approach for learning representations for correspondence from raw video, based on training a random walker to walk along cycles on a space-time graph. Despite its simplicity, the method achieves state-of-the-art performance among self-supervised methods on video object segmentation, and part and pose propagation. We view this work as a step toward scaling up self-supervised representation learning to the challenges of large-scale unlabelled video data, including gracefully adapting to new data in an online manner. Moreover, we hope this paper provides insight for further study of representation learning with latent positives.

## 6 Broader Impact

Research presented in the paper has a potential to positively contribute to a number of practical applications where establishing temporal correspondence in video is critical, among them pedestrian safety in automotive settings, patient monitoring in hospitals and elderly care homes, video-based animal monitoring and 3D reconstruction, etc. However, there is also a potential for the technology to be used for nefarious purposes, mainly in the area of unauthorized surveillance, especially by autocratic regimes. As partial mitigation, we commit to not entering into any contracts involving this technology with any government or quasi-governmental agencies of countries with an *EIU Democracy Index* [20] score of 4.0 or below (“authoritarian regimes”), or authorizing them to use our software.

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## A Comparison to Supervised Methods on DAVIS-VOS

The proposed method outperforms many supervised methods for video object segmentation, despite relying on a simple label propagation algorithm, never being trained for object segmentation, and never training on the DAVIS dataset.

Method	Backbone	Train Data (#frames)	$\mathcal{J} \& \mathcal{F}_m$	$\mathcal{J}_m$	$\mathcal{J}_r$	$\mathcal{F}_m$	$\mathcal{F}_r$
OSMN [93]	VGG-16	I/C/D (1.2M + 227k)	54.8	52.5	60.9	57.1	66.1
SiamMask [85]	ResNet-50	I/V/C/Y (1.2M + 2.7M)	56.4	54.3	62.8	58.5	67.5
OSVOS [10]	VGG-16	I/D (1.2M + 10k)	60.3	56.6	63.8	63.9	73.8
OnAVOS [82]	ResNet-38	I/C/P/D (1.2M + 517k)	65.4	61.6	67.4	69.1	75.4
OSVOS-S [51]	VGG-16	I/P/D (1.2M + 17k)	68.0	64.7	74.2	71.3	80.7
FEELVOS [81]	Xception-65	I/C/D/Y (1.2M + 663k)	71.5	69.1	79.1	74.0	83.8
PReMVOS [49]	ResNet-101	I/C/D/P/M (1.2M + 527k)	77.8	73.9	83.1	81.8	88.9
STM [59]	ResNet-50	I/D/Y (1.2M + 164k)	81.8	79.2	-	84.3	-
<b>Ours</b>	ResNet-18	K ( $\bar{20}$ M unlabeled)	67.6	64.8	76.1	70.2	82.1

Table 3: **Video object segmentation results on DAVIS 2017 val set.** We show results of state-of-the-art **supervised** approaches in comparison to our unsupervised one (see main paper for comparison with unsupervised methods). Key for *Train Data* column: I=ImageNet, K=Kinetics, V = ImageNet-VID, C=COCO, D=DAVIS, M=Mapillary, P=PASCAL-VOC Y=YouTube-VOS.  $\mathcal{F}$  is a boundary alignment metric, while  $\mathcal{J}$  measures region similarity as IOU between masks. Note that our method beats half the supervised approaches, despite seeing no labels.

## B Using a Single Feature Map

We follow the simplest approach for extracting nodes from an image without supervision, which is to simply sample patches in a convolutional manner. The most efficient way of doing this would be to only encode the image once, and pool the features to obtain region-level features [46].

We began with that idea and found that the network could cheat to solve this dense correspondence task even across long sequences, by learning a shortcut. It is well-known that convolutional networks can learn to rely on boundary artifacts [46] to encode position information, which is useful for the dense correspondence task. To control for this, we considered reducing the receptive field of the network to the extent that entries in the center crop of the spatial feature map do not see the boundary; we then cropped the feature map to only see this region. We also considered randomly blurring frames in each video to combat space-time compression artifacts, as well as considering *random* videos – made of noise. Surprisingly, the network was able to learn a shortcut in each case. In the case of random videos, the shortcut solution was not as successful, but we still found it surprising that the self-supervised loss of Equation 5 could be optimized at all.

## C Additional Ablation

**Effect of frame-rate at training time** We ablate the effect of frame-rate (i.e. frames per second) used to generate sequences for training, on downstream object segmentation performance. The case of infinite frame-rate corresponds to the setting where the *same* image is used in each time step; this experiment is meant to disentangle the effect of data augmentation (spatial jittering of patches) from the natural “data augmentation” observed in video. We observe that spatio-temporal transformation is beneficial for learning of representations that transfer better for object segmentation.

Frame rate	$\mathcal{J} \& \mathcal{F}_m$
2	65.9
4	67.5
8	67.6
30	62.3
$\infty$	57.5

## D Hyper-parameters

We list the key hyper-parameters and ranges considered at training time. We did not tune the patch extraction strategy and the majority of hyper-parameters. The hyper-parameters varied, namely edge dropout and video length, were ablated in Section 3 (shown in bold). Note that the training path length is twice that of the video sequence length (since we construct a palindrome).

- Learning rate: {0.0001}
- Temperature  $\tau$ : {0.07}
- Dimensionality  $d$  of embedding: {128}
- Frame size: {256}
- Video length: {2, 4, 6, 10}
- Edge dropout: {0, 0.1, 0.2, 0.3}
- Frame rate: {2, 4, 8, 30}
- Patch Size: {64}
- Patch Stride: {32}
- Spatial Jittering (crop range): {(0.7, 0.9)}

**Hyper-parameters for Label Propagation (Test):** Here, bold denotes setting used in experiments.

- Temperature: {0.07} (same as training)
- Number of neighbors: {10, 20}
- Number of context frames: {varies per task}
- Radius on feature map considered for source nodes: {12, 20}

## E Test-time Training Details

We adopt the same hyper-parameters for optimization as in training: we use the Adam optimizer with learning rate 0.0001. Given an input video  $I$ , we fine-tune the model parameters by applying Algorithm 1 with input frames  $\{I_{t-m}, \dots, I_t, \dots, I_{t+m}\}$ , *prior* to propagating labels to  $I_t$ . For efficiency, we only finetune the model every 5 timesteps, applying Adam for 100 updates. In practice, we use  $m = 10$ , which we did not tune.

## F Utility Functions used in Algorithm 1

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**Algorithm 2** Utility functions.

---

```
// psizes : size of patches to be extracted
import torch
import kornia.augmentation as K

# Turning images into list of patches
unfold = torch.nn.Unfold((psize, psize), stride=(psize//2, psize//2))

# L2 normalization
l2_norm = lambda x: torch.nn.functional.normalize(x, p=2, dim=1)

# Slightly cropping patches once extracted
spatial_jitter = K.RandomResizedCrop(size=(psize, psize), scale=(0.7, 0.9), ratio=(0.7, 1.3))
```

---