Abstract. This paper presents TCE: Temporally Coherent Embeddings for self-supervised video representation learning. The proposed method exploits inherent structure of unlabeled video data to explicitly enforce temporal coherency in the embedding space, rather than indirectly learning it through ranking or predictive pretext tasks. In the same way that high-level visual information in the world changes smoothly, we believe that nearby frames in learned representations should demonstrate similar properties. Using this assumption, we train the TCE model to encode videos such that adjacent frames exist close to each other and videos are separated from one another. Using TCE we learn robust representations from large quantities of unlabeled video data. We evaluate our self-supervised trained TCE model by adding a classification layer and finetuning the learned representation on the downstream task of video action recognition on the UCF101 dataset. We obtain 68.7% accuracy and outperform the state-of-the-art self-supervised methods despite using a significantly smaller dataset for pre-training. Notably, we demonstrate results competitive with more complex 3D-CNN based networks while training with a 2D-CNN network backbone on action recognition tasks.

1 Introduction

Many state of the art image and video deep learning approaches have heavily relied on fully-supervised methods along with the abundance of manually annotated datasets. However obtaining labels for many tasks is impractical and not scalable, especially when considering the ambiguities in complex data sources such as videos or point clouds.

Self-Supervised Learning (SSL) is a new and promising paradigm, where a model is trained on unlabeled data based on a learning signal constructed from inherent structure in the training sample. With SSL it is possible to leverage enormous amounts of unlabeled data to learn robust representations of images and videos. These methods are often pre-trained on large-scale unlabeled image or video data with specific upstream (i.e., proxy or pretext) tasks and then fine-tuned to adapt to downstream tasks. Learned representations from unlabeled images
Fig. 1: Overview of TCE: Temporally Coherent Embeddings for self-supervised video representation learning. We train an embedding function to encode videos such that adjacent frames exist close to each other and videos are separated from one another. At each step relative attraction and separation is achieved by contrasting an anchor frame and those adjacent to N randomly sampled negative examples from other videos.

have been shown to successfully transfer to multiple downstream tasks such as image classification \[2,5,38\] and object detection \[12,23\], in some cases successfully outperforming fully-supervised methods \[5\]. However, self-supervision from videos is still not very effective for downstream tasks such as action recognition \[14\] and dense correspondences \[8\] despite videos being a rich source of self-supervision.

Current state of art approaches for self-supervised representation learning from videos fall into two categories: ranking methods \[9,10,22,25,29,50\], and predictive methods \[14,27,28,36,42,41\]. Ranking methods randomly shuffle subsequent frames or clips from a video, and solve pretext tasks related to determining the original order. Predictive methods can be grouped into two categories: those that predict a pixel level reconstruction of future frames \[27,28,36,42\], and those that predict latent representations of future frames in the embedding space \[14,41\]. However, for both ranking and predictive methods the use of hand-designed pretext tasks can lead to shortcomings when transferring the learnt embeddings to downstream tasks. El-Nouby et al. \[9\] and Kim et al. \[22\] demonstrate that trivial solutions and noisy pseudo-labels can hinder the generalisability of ranking approaches to downstream tasks. Pixel-space predictive methods are limited by the need to predict the low-level details of frame pixels \[16\]. In contrast, predictive methods are designed to predict the embedding of the future frames based on the recent past. However, they are still limited by the fact that the future is not deterministic \[14\].

Our approach to the problem of self-supervised representation learning from videos is motivated by the question: What properties are desirable in an embedding space for the downstream task of video action recognition? We believe one of
essential properties of learned representations from videos is temporal coherency. High-level visual information in the world changes smoothly and consistently, and we believe that adjacent frames in a learned embedding space should behave in a similar fashion. Inspired by recent advances in self-supervised learning in the image domain [25] we introduce Temporally Coherent Embeddings (TCE), a contrastive loss function designed to learn a temporally coherent embedding space from unlabeled videos. Instead of using hand-designed heuristics to implicitly learn coherency by ordering or predicting frames, our approach employs a contrastive loss to explicitly enforce coherency in the embedding space by encouraging similarity in the embeddings of temporally adjacent frames without any labels. Our proxy loss consequently learns an embedding space in which high-level visual information changes in a smooth and gradual fashion over time, leading to improved downstream performance on video action recognition. We summarize our contribution as follows:

- We propose TCE: Temporally Coherent Embeddings for self-supervised video representation learning. Our method exploits the structure of video data to explicitly enforce temporal coherency in the embedding, rather than indirectly learning it through ranking or predictive tasks.
- In order to demonstrate the quality of our learned representations, we show state-of-the-art results on the UCF101 action recognition dataset for networks pre-trained using unlabeled videos from UCF101, outperforming all the previous more complex 3D-CNN based networks and highly competitive results against networks pre-trained using the large scale Kinetics400 dataset.

2 Related Works

Deep neural networks have shown strong results in computer vision tasks such as image classification, object detection and segmentation by leveraging large, publicly available labeled datasets [4,26,49]. However, the lack of labeled data is a limiting factor in the applicability of deep learning to many target problem domains such as action recognition. Prior work [37] establishes a roughly logarithmic relationship between the quantity of data used for training and the performance of a network; however, labeling data is a time consuming and expensive process. Consequently, a large body of work has emerged which seeks to leverage the huge quantities of unlabelled, publicly available data. These works typically define a pretext task for which the supervisory signal to learn a data representation can be obtained without hand-labelling. The learned representation with self-supervision are then fine-tuned to adapt to one or more downstream tasks with a reduced dependence on data quantity.

2.1 Self-Supervised Learning from Images

There are many different approaches to learning from unlabeled images which can be categorised into contrastive and generative methods [12]. Generative
methods learn a representation of the data which allows the prediction of missing components of the data. Common examples include predicting a color image from its grey scale counterpart \[43, 51\] and using the reconstruction signal from auto-encoders to produce a self-supervised encoder \[33, 40, 52\]. However, as these methods are trained on a per pixel basis, they have been shown to produce features that do not transfer to other downstream tasks very well \[52\].

Other methods have encouraged higher level features by splitting the training image into a series of patches. For example \[6\] learns representations by predicting the relative position of two patches within an image, while \[31\] learns representations by extracting multiple tiles from the training image and shuffling them into one of a number of predefined permutations to make jigsaw puzzles. Other notable approaches have predicted image rotations without reference to the original image \[11\], and discrimination between a patch taken from a training image and surrogate classes created by applying a family of transformations to that patch \[7\].

Conversely to generative methods, contrastive approaches build representations by modelling the differences and similarities between two or more inputs. In these methods, negative examples are required to contrast against \[2, 16, 18, 32, 34, 38\]. The key differences between generative and contrastive methods is the calculation of the error used for training and its implication on the learned representation. Predictive methods compute the error in the pixel space whereas contrastive methods form a loss term in the embedding space. Contrastive methods tend to be able to learn more abstract, latent representations as a result because pixel level loss functions commonly assume independence between pixels and rely on pixel level details such as colour.

Recently, contrastive methods have been successful in static image representation learning. Approaches in \[18\] and \[2\] maximise mutual information (MI) between local and global features, respectively. Mutual information maximisation has featured in numerous unsupervised feature learning approaches \[2, 16, 18, 32, 34, 38\]. Several formulations of MI, including those based on Kullback-Leibler (KL) and Jensen-Shannon (JSD) divergences, have been proposed over the years \[3, 18, 47\]. However, recent developments in this area have shown significant performance boosts proportional to the number of negative examples used in training \[2, 30, 38, 39\]. Processing such numbers of negatives is generally only tractable when employing an approximation of MI such as Noise Contrastive Estimation (NCE) or its variations \[13\]. Tian et al. \[38\] propose to learn embeddings by contrasting between different colours spaces of the same image, training a separate network on each colourspace. They also expand their proposed system to different frames of videos. In this case, their optimisation objective is mathematically similar to what we present here. However we train only a single network and consequently present significant improvements on downstream task performance.
2.2 Self-Supervised Learning from Video Data

Videos, in contrast to still images, provide a valuable temporal structure that can be leveraged as an additional training signal for self-supervision. Recent SSL approaches for video data can be classified into ranking and predictive methods. Ranking methods learn to solve pretext tasks to recover the temporal order of shuffled video frames. Many such approaches \[10,29\] learn representations by classifying whether or not a series of input frames are presented in chronological order. Lee et al. \[25\] take this approach a step further and, instead, sort sequences of frames as a pretext task to learn representations, taking an input of four frames and determining their chronological order. Several methods further extend this method of sequence sorting with 3D CNNs to sort sequences of clips taken from the video instead of sorting single frames \[9,22,50\]. These methods achieve higher performance on downstream tasks than their 2D CNN predecessors.

Predictive methods can be grouped in two sub-categories, representative and reconstructive. Vondrick et al. \[41\] and Han et al. \[14\] predict latent representations of future video frames similar to the aforementioned generative SSL methods for static images. The 3D-CNN based architecture proposed by Han et al. \[14\] is currently the state of the art for self-supervised representation learning as demonstrated on the task of action recognition for the UCF101 dataset. The high performance and representation ability of 3D CNN architectures, shown in several self-supervised predictive methods and ranking methods, is not without significant computational cost. Han et al. \[14\] note that their model took six weeks to train on the Kinetics400 dataset and four Nvidia P40 GPUs. A number of methods have also attempted to reconstruct future video frames rather than future latent representations \[27,28,36,42\]. The representation ability of reconstructive methods is constrained by their requirement to predict pixel level details of images. This leaves such methods less likely to model abstract, semantic features and hence less likely to transfer to downstream tasks \[14,16\].

Several previous methods have also explored the idea of temporal coherency as a signal for self-supervision. Jayaraman et al. \[20\] propose using temporal coherence as an auxiliary signal for semi-supervised learning from videos. Wang et al. \[45\] uses a triplet loss formulation to learn coherence between patches across frames, though they use a kernelized correlation filter \[17\] to ensure similarity between the positive examples. Sermanet et al. \[34\] also employ a triplet and n-pair loss formulation to learn video representations. Their approach learns from viewpoints of the same action taken from either different videos or different frames in the same video. Such a constraint on the training data encourages their model to learn viewpoint invariant features for different actions. However their loss formulation contrasts only one negative with the positive pair at any time, which does not leverage the advantages found in using multiple negatives described by \[2,30,38,39\]. Furthermore their learnt model is trained on only one class of videos and is not tested on diverse action recognition datasets with multiple classes, such as UCF101 \[35\] or HMBD51 \[24\]. Conversely, our method leverages multiple negatives from a number of diverse videos on a publicly available dataset. Hence, TCE has a wider range of data that could be used. Finally, Isola et al. \[19\] train a
simple classifier to detect whether or not frames taken from a video occur within a given time frame of one another. We show in this work that our method extends previous attempts to use temporal coherency for SSL by leveraging contrastive methods to attract frame embeddings without using a supervised signal or relying on priors such as trackers to assist our selection of positive examples.

3 Methodology

We propose a simple framework to learn a temporally coherent embedding space from unlabeled videos. The mathematical formulation of our method, TCE: Temporally Coherent Embeddings for self-supervised video representation learning, is explained in this section.

3.1 Temporal Coherency Training

The goal of our proposed method, TCE, is to explicitly enforce coherency in the embedding space by encouraging similarity in the embeddings of temporally adjacent frames without any labels.

To develop representations which are coherent in time, we seek to learn an embedding function $f(.)$ which transforms a video frame $x^t_i$ from pixel-space into a lower dimensional embedding space. We adopt the shorthand notation $f(x^t_i) := f^t_i$ for the transformed frame.

We define temporal coherency as minimisation of the temporal derivatives of the representations in embedding space. First-order temporal coherence in the embedding space is thus achieved when $\frac{\partial f^t_i}{\partial t} \approx 0$, and can be extended to the $n^{th}$ order by requiring $\frac{\partial f^n_i}{\partial_n t} \approx 0$ [20].

To the first order, coherence is maximised by minimising a distance function $d(f^t_i, f^t_{i+1})$ between two temporally adjacent frames in the same video, as $\frac{\partial f^t_i}{\partial t} \propto f^t_{i+1} - f^t_i$. A trivial solution to this optimisation goal is apparent: an embedding function which simply maps all inputs to the same point in representation space. To avoid such a trivial solution, a number of existing approaches adopt a contrastive learning paradigm rather than simply minimising $d(f^t_i, f^t_{i+1})$. One such approach is to formulate a triplet loss paradigm that also seeks to maximise distance to some negative frame representations [20]. This triplet loss is:

$$L = \mathbb{E} \left[ d(f^t_i, f^t_{i+1}) + \max (\delta - d(f^t_i, f^n), 0) \right],$$ (1)

where $\mathbb{E}$ denotes the expectation value, in this case over a set positive pairs of frames. $f^n$ is the negative frame representation and $\delta$ is some distance margin which $d(f^t_i, f^n)$ should be greater than in order to minimise the loss. In this paradigm, the two temporally adjacent frames are considered positive examples.

Rather than minimise distance between frame representations, an alternative formulation is to maximise a similarity metric between representations, $s(f^t_{i+1}, f^t_i)$. A similarity-maximising alternative to Equation (1) is to minimise this loss function:
\[
\mathcal{L} = -\mathbb{E}[s(f_{t+1}, f_t) - \min(\delta - s(f_t, f_n), 0)]
\]  

(2)

A suitable similarity function is the inner product between \(l_2\) normalized representations: \(s(f_{t+1}, f_t) = f_{t+1}^T f_t\). This similarity function is minimised when \(f_{t+1} = f_t\), at which point the distance is also minimised. In the supplementary materials, we show that minimising distance between \(l_2\) normalised features will always increase their inner product at all stages during optimization.

Inspired by other works which show that leveraging multiple negative examples can lead to improved performance on a number of tasks \([12,16,30]\), we improve upon the triplet loss in Equation 2 by formulating the task as a binary classification between one positive and \(N\), a set of \(N\) negative examples.

Consider a video dataset where each video \(\mathcal{V}^i\) contains \(T^i\) frames \(\{x^i_1, x^i_2, ..., x^i_{T^i}\}\). We consider a pair of temporally neighbouring frames from one video as positive examples, and consider all frames from other videos to be negative examples. We sample these negative examples to form a set \(\mathcal{N}\) containing \(N\) frames. We adopt a standard cross-entropy loss in Equation 3 which is minimised when \(s(f_t, f_{t+1})\) is large and \(s(f_t, f_n)\) is small for all \(x_n \in \mathcal{N}\), as per similar works in \([14,30,32]\).

\[
\mathcal{L}_{1st}(x^i_{t+1}, x^i_t, \mathcal{N}) = -\mathbb{E} \left[ \log \frac{e^{s(f_t, f_{t+1})}}{e^{s_1(f_t, f_{t+1})} + \sum_{N} e^{s(f_t, f_n)}} \right]
\]  

(3)

Minimising this loss function is analogous to training a binary classifier to correctly select the positive example from all negative examples in \(\mathcal{N}\).

### 3.2 Higher Order Coherency

To the first order, the coherency objective will encourage neighbouring video frames to cluster in representation space because it penalises large distances between frames in the embedding space. Additional temporal structure in the embeddings can be captured through higher order coherency. For example, a second-order coherency objective is one which, in addition to minimizing the first-order derivative of embedding vectors with respect to time, has the optimization goal of setting \(\partial^2 f_t/\partial t^2 \approx 0\). This optimization goal is accomplished when \(f_{t+2} - f_{t+1} \approx f_{t+1} - f_t\).

By extending the coherency objective to second-order the optimization goal is changed from clustering temporally adjacent frame embeddings to also clustering the differences between those embeddings. Clustering the differences between embeddings ensures that the direction that the embeddings travel does not significantly vary over short time periods, resulting in trajectories that are more smooth. The second-order cross-entropy loss is:

\[
\mathcal{L}_{2nd} = -\mathbb{E} \left[ \log \frac{e^{s_2(f_t, f_{t+1}, f_{t+2})}}{e^{s_2(f_t, f_{t+1}, f_{t+2})} + \sum_{N_2} e^{s_2(f_t, f_{t+1}, f_n)}} \right],
\]  

(4)
where \( s_2(f_{t+2}, f_{t+1}, f_t) \) is a modified version of the similarity function acting on the differences between the three temporally adjacent frames. That is, 
\[
s_2(f_t, f_{t+1}, f_{t+2}) = s(f_{t+1} - f_t, f_{t+2} - f_{t+1})
\]
We also stress that the negative examples used in calculating the second-order cross-entropy loss are distinct from those used when calculating first-order loss. Most notably, the second-order coherency objective seeks to cluster differences between embeddings rather than the embeddings themselves and so sampling negative examples from other videos does not provide sufficiently difficult negative examples to learn from. For this reason, negative samples in \( \mathcal{N}_2 \) are sampled within the same video as the positives.

The coherency objective described can be extended to higher order derivatives trivially by defining the appropriate similarity function. In the general case, the similarity function for the \( n \)th order derivative can be recursively defined as
\[
s_n(f_{t+n}, ..., f_t) = s_{n-1}(f_{t+n} - f_{t+n-1}, ..., f_{t+1} - f_t).
\]

### 3.3 Leveraging Multiple Negative Examples with Noise Contrastive Estimation (NCE)

For large numbers of negative examples, calculating the normalization factor for the full softmax distribution in Equation 3 can prove computationally intractable. Noise Contrastive Estimation (NCE) [13] is a computationally efficient means of estimating unnormalized statistical models and performing logistic regression to discriminate between observed data and a noise distribution. In this case, discriminating between the positive and negative examples.

The posterior probability that a given pair of embeddings belong to the data distribution \( C \) – that is, they are a pair of positive examples – is:
\[
P(C|x_1, x_2) = \frac{P(x_2|x_1)}{P(x_2|x_1) + NP_n(x_2|x_1)}, \tag{5}
\]
where \( P(x_2|x_1) \) is the probability that \( x_2 \) is a positive example from the data distribution given \( x_1 \), and \( P_n(x_2|x_1) \) is the probability that it is a negative example taken from the noise distribution. Any noise distribution can be chosen so long as it is computationally easy to sample from and does not assign zero probability to any frame \( x_2 \). Akin to [30,38], we choose a uniform distribution such that \( P_n(x_2|x_1) = 1/N \quad \forall x_2 \in \mathcal{N} \). The similarity function \( s_1 \) can be converted to a probability describing the probability of a second frame \( x_2 \) being a positive for the given frame \( x_1 \), by exponentiating and normalizing:
\[
P(x_2|x_1) = \frac{e^{s_1(f_1, f_2)}}{e^{s_1(f_1, f_2)} + \sum_{\mathcal{N}} e^{s_1(f_1, f_n)}} \tag{6}
\]
With NCE, the posterior probability in Equation 5 is instead estimated from the unnormalized similarity distribution from the model, so that it can instead be written:
\[
P(C|x_1, x_2) = \frac{e^{s(f_1, f_2)}}{e^{s(f_1, f_2)} + NP_n(x_2|x_1)} \tag{7}
\]
The NCE based approximation of the optimization goal of the model can be adapted from Equation 3. It is simple to minimise the negative log-posterior probability in Equation 7.

\[ \mathcal{L}_{NCE} = -\mathbb{E}_{x,x_p} \left\{ \log P(C|x;x_p) \right\} + N \mathbb{E}_{x_n \in \mathcal{N}} \left[ \log P(\tilde{C}|x;x_n) \right], \] (8)

where \( P(\tilde{C}|x;x_n) = 1 - P(C|x;x_n) \) is the probability of correctly classifying a sample from the noise distribution.

4 Experimental Results

In this section we evaluate the performance of our proposed method in a number of ways. We trained a classification network on an action recognition task using the self-supervised learned representation. We investigate the effect that training with multiple negatives has on results, in addition to the method of network initialization, and the effects of enforcing higher order temporal coherency. We also directly evaluate the features that our method produces against those from other training methods including ImageNet pretraining.

4.1 Dataset

TCE is a generalised method of learning robust representations of video data. Here we focus on the task of video action recognition. Specifically, we train and evaluate TCE on the UCF101 dataset [35]. Containing 101 human action classes and 13,000 videos, UCF101 is a common benchmark dataset for both action recognition as well as many self-supervised approaches. Three different train/test splits were released with the data. Aligning with self-supervised methods [50, 29] and [9], we train and evaluate on the first train/test split.

4.2 Self-Supervised Training

We train an embedding function on the UCF101 dataset without labels to learn robust video representations. The network architecture on which we train is ResNet-50 [15]. We initialize the network with random weights and train for a total of 9 epochs with 4 Tesla-V100 GPUs. Training is completed using a stochastic gradient descent optimiser and batch size of 100. Initially a learning rate of 0.03 is used and reduced by a factor of 10 after 5 epochs. Positive examples are taken by sampling two adjacent video frames from the dataset, and each frame in the dataset is used as a positive example once per epoch. During training, frames are resized so that the shortest side is 256 pixels while preserving image scale, and are then randomly cropped to a 224 × 224 window. Random horizontal flipping is also employed.

\( N_1 = 2048 \) negative samples used in optimizing first order coherency are drawn from randomly selected videos in the dataset, excluding the video from which positive examples were drawn. Our rationale behind this sampling regime...
is that by sampling from videos other than the positive embeddings, we ensure
our negatives are significantly different in appearance. For higher order coherency
experiments, $N_2 = 100$ negative examples are sampled from within the same
video as the positive examples are drawn. $N_2$ is significantly smaller than $N_1$
as the number of frames available in a single video is significantly smaller than
those in the rest of the dataset.

Inspired by Wu et al. [48], we maintain a memory bank to store embeddings
for each frame in the dataset to efficiently retrieve noisy samples without re-
computing their embeddings. The memory bank is dynamically updated with
the new embeddings on every forward pass of the network.

### 4.3 Action Recognition

**Training** We benchmark the quality of our learned embedding function by
finetuning our network for action recognition on the UCF101 [35] dataset, which
contains in excess of 13,000 videos of 101 action classes. Following [29,9,50] we
perform experiments and report on the first test/train split of the dataset.

During training, we replace the final fully connected layer of our pretrained
network with another fully-connected layer of 101 nodes, using the ReLu activation
function. We employ the stack-of-differences video-clip encoder introduced by
[10]. Six neighbouring frames are taken from the video to produce an input with
size $224 \times 224 \times 15$ by resizing each image to $224 \times 224$ pixels and taking the
differences between the five neighbouring pairs of frames. The convolutional
layers of our pretrained network are duplicated five times in order to allow the
15-channel input to be fed through the network.

During evaluation, nineteen evenly-spaced blocks of six frames are taken
from each video. Softmax outputs on each block of frames are averaged, and
the highest average value is the classification output for the video. We report
results for the highest scoring epoch during training for all our experiments. The
network is trained using 4 Tesla-V100 GPUs and stochastic gradient descent for
600 epochs with a learning rate of 0.05 that is decayed by a factor of 10 after
350 epochs.

**Comparison to State-of-the-Art** The results of our training method are
compared against other state-of-the-art results in Table 1. We achieve higher
Top-1 classification accuracy with pretraining on the UCF101 dataset than any
other approach in the literature which trains on the same dataset, as far as we
are aware. Notably this is irrespective of network architecture and our approach
implemented on ResNet50 outperforms Video Clip Ordering [50] – which uses
3D ResNet18 as the network backbone – by 3.8% despite being implemented on
a 2D convolutional network.

Our approach also surpasses the vast majority of the those pre-trained on the
Kinetics400 dataset despite using a significantly smaller dataset for pre-training.
The only approach in the literature which surpasses our result is Dense Predictive
Coding (DPC) [14] which is both trained on the Kinetics400 [4] - which contains
Table 1: Top-1 accuracy performance for action recognition task on UCF101 dataset. * Network architecture using stack-of-differences for downstream training. ** Two networks which do not share weights. † Results reported on train/test split 1 of UCF101.

| Method                        | Backbone  | 2D-CNN | Pre-Training UCF101 (%) |
|-------------------------------|-----------|--------|-------------------------|
| Motion & Appearance [44]      | C3D       | ×      | Kinetics400 61.2         |
| 3DRotNet [21]                 | 3D ResNet-18 | ×    | Kinetics400 62.9       |
| 3DCubicPuzzles [22]           | 3D ResNet-18 | ×    | Kinetics400 65.8       |
| DPC [14]                      | 3D ResNet-18 | ×    | Kinetics400 68.2       |
| DPC [14]                      | 3D ResNet-34 | ×    | Kinetics400 75.7       |
| Shuffle and Learn [29]†       | AlexNet   | ✓      | UCF101 50.9            |
| VideoGAN [42]                 | C3D       | ×      | UCF101 52.1            |
| Arrow of time [46]            | AlexNet   | ✓      | UCF101 55.3            |
| OPN [10]                      | AlexNet   | ✓      | UCF101 56.3            |
| CMC [38]                      | CaffeNet ×2** | ✓    | UCF101 59.1           |
| Motion & Appearance [44]      | C3D       | ×      | UCF101 58.8            |
| O3N [10]                      | AlexNet*  | ✓      | UCF101 60.3            |
| DPC [14]                      | 3D ResNet-18 | ×    | UCF101 60.6            |
| Skip-Clip [9]†                | 3D ResNet-18 | ×    | UCF101 64.4            |
| Video Clip Ordering [50]†     | R3D       | ×      | UCF101 64.9            |
| **TCE (Ours)**†               | ResNet-50* | ✓      | UCF101 68.7            |

306K video clips, as opposed to only 13K for UCF - and employs the extremely high capacity 3D ResNet-34 network architecture. Notably, DPC’s network took six weeks to train [14], while our approach completed pre-training and fine-tuning on action recognition within four days. We plan to explore use of Kinetics400 in future work to demonstrate the scalability of our method to larger datasets.

4.4 Analysis of Results

In this section we detail experiments to analyse the performance of TCE. We compare our results to random network initialization and ImageNet pretraining in order to gauge how our choice of network architecture and loss function impacts the performance of the downstream action-recognition task, and also investigate how changing the number of negatives sampled affects performance. Finally, we investigate how higher order coherency objectives affect the results achieved.

Comparison to Random Initialization Table 2 details the performance achieved by our network on the action recognition task when trained from randomly initialized weights, ImageNet pretrained weights, and our self-supervised representation, TCE.

We report a 14.9% improvement over training from random weights and achieve 88.5% of the ImageNet pretraining baseline. This significant improvement demonstrates that our embedding space learns features which generalise well to the task of action recognition and further validates TCE against the standard
Table 2: Top-1 accuracy performance for action recognition task on UCF101 dataset for different initialization methods of our network.

| Initialization  | UCF101 |
|----------------|--------|
| Random         | 59.82  |
| ImageNet       | 77.69  |
| TCE (Ours)     | 68.75  |

Fig. 2: Top-1 Accuracy on UCF101 action recognition task versus the number of negative examples used during training.

...approach of full supervision. Notably, the combination of ResNet50 and stack-of-differences in the downstream task achieves 59.82% accuracy after training with randomly initialized weights, well above results on AlexNet quoted in [10, 29, 46].

Investigating the Effects of Negative Samples

We also investigated how the number of negative examples sampled when calculating first-order cross-entropy loss affect performance on the action recognition downstream task. Fig. 2 illustrates the relationship between the number of negative examples sampled, and the Top-1 classification accuracy on the action recognition classification task. We found that increasing the number of negatives examples used improved Top-1 Accuracy up to a value of 2048 negatives, after which adding additional negatives caused performance to decline.

Investigating the Effects of High-Order Coherency Objectives

We investigate the effect of implementing a higher-order loss term to TCE, with results presented in Table 3. The First + Second Order result is trained on a total loss which is the sum of the first-order coherency loss introduced in Equation 3 with the second-order loss introduced in Equation 4.

Table 3: Action recognition performance on UCF101 when training TCE with and without enforcing a second-order coherency.

| Method                | UCF101 |
|-----------------------|--------|
| First Order Only      | 67.46  |
| First + Second Order  | 66.35  |
In both training cases, we pretrain on UCF101 with $N_1 = 4096$ and $N_2 = 100$ negatives when calculating first and second-order loss terms respectively. $N_2$ is lower than $N_1$ as the number of frames available in a single video is significantly smaller than those in the rest of the dataset.

We found that implementing a higher order coherency term to the loss function resulted in diminished downstream performance for action recognition, compared to simply training with first-order loss. We believe that this is because the within-video negative examples are too similar to the positive examples and act as noise when learning, hindering the overall performance. Other methods which leverage negative examples from within-video introduce a temporal buffer to ensure that negative examples are temporally distant to the positive examples and so are easier for the network to distinguish during training. We have included a similar study in the supplementary materials.

### 4.5 Evaluating Our Embeddings

In this section we qualitatively evaluate the effectiveness of $TCE$ in creating a temporally coherent embedding space. We visualise our embedding space by using t-SNE to reduce our frame embeddings to two dimensions, so that each point in the graph represents a single frame. We use a color map to show the temporal order of frames for figures containing only a single video.

#### Coherence during Training

Fig. 3 visualises the evolution of our embedding space over the course of training. Our training increases the temporal coherency of the embedding space across epochs, from almost no coherency for random weights in (a) to partial coherency at four epochs in (b) and very strong coherency at nine epochs in (c). t-SNE is used to reduce the dimensionality of the embeddings for plotting. Each point on the graph represents a different frame of the video. During training, our method successfully learns an embedding function which produces temporally coherent frame embeddings from a single video.
Fig. 4: Comparison between frame embedding on one video (Bowling class) in UCF101 with TCE (a); ImageNet pretraining (b); and DPC [14] (c).

Fig. 5: t-SNE visualisation of UCF101 frame embeddings produced with TCE. Ten random videos from five classes in the UCF101 validation set are represented.

Comparison to other methods Figure 4 compares visualisations of our embedding space against an ImageNet pre-trained checkpoint and DPC [14]. Implementation details for how we obtained the t-SNE for DPC can be found in the supplementary materials. Our method demonstrates significantly better coherency than both ImageNet and DPC, with frames over time forming a coherent path with no major discontinuities.

Class Clustering Fig. 5 plots ten videos from five classes taken from the UCF101 validation set, with each point in the t-SNE representing a single frame. We observe a clear separation between videos in the embedding space, and strong separation between different action classes.

5 Conclusion

In this paper, we have presented an approach to learn embeddings from unlabelled videos, TCE: Temporally Coherent Embeddings. Specifically, we train our model
in a self-supervised manner by leveraging the temporal information embedded in video data and enforcing coherency in the embedding space. At each step relative attraction and separation is achieved by contrasting an anchor frame and those adjacent to N randomly sampled negative examples from other videos. We applied the learned representation to the downstream task of video action recognition. Our method outperforms previous 2D-CNN self-supervised learning approaches by 8%, using UCF101. We achieve 68.7% accuracy, despite using a significantly smaller dataset for pre-training. Most importantly, our results reveal that our model delivers competitive generalization results without the complexity of 3D-CNN network architecture. We believe this shows that explicitly enforcing temporal embedding coherency between nearby frames is a powerful learning signal for action recognition, resulting in models that are required smaller computational training capacity and are faster at inference time. For future work we plan on investigating transfer learning of pre-trained TCE for downstream tasks that require a level of temporal understanding, such as robotic perception.

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6 Supplementary Material

In this section we provide appendices to supplement the material of the main paper. Appendix A contains the proof that minimising the distance between $l_2$ normalized vectors always increases the inner product. Appendix B contains a study on the impact using a margin around our anchor positive to exclude frames from consideration for negative examples and Appendix C outlines the method we used to obtain the t-SNE of Dense Predictive Coding \[14\] in Figure 4.

6.1 Appendix A: Proof that minimising distance between $l_2$ normalised vectors increases inner product

This section provides proof that any optimisation task which maximises the inner product of two $l_2$ normalized vectors will also minimise distance between those points. The $l_2$ distance between two $l_2$ normalized vectors $u$ and $v$ can be written as a function of the inner product as follows:

$$d_{l_2}^2(u, v) = ||u - v||^2 = u^T u + v^T v - 2u^T v = 2(1 - u^T v) \quad (9)$$

The change in distance with respect to the inner product is then:

$$\frac{\partial d_{l_2}}{\partial u^T v} = -\sqrt{\frac{1}{2(1 - u^T v)}} \quad (10)$$

Note that this derivative is always negative, meaning distance monotonically decreased as the inner product increases. Thus an optimisation goal which maximises inner product between $l_2$ normalized vectors is equivalent to one which minimises distance.

6.2 Appendix B: Temporal Buffer in second order coherency

Inspired by [34], we experiment with adding a temporal buffer around our anchor positive when training with second order coherency. Video frames within a margin of $m$ frames of the anchor positive are excluded from the pool of potential negatives when randomly sampling in-video negative examples for second order coherency. We implemented a margin value of 10 frames which resulted a drop in performance of roughly 2% on action recognition task. We hypothesise that this is due to the fact that [34] uses a triplet loss where the location of a single negative example used has a significant impact on the success of their training. However, as our method uses 100 negative examples sampled from within the video, our performance is more heavily impacted by reducing our pool of potential negative examples than it is by any potential improvement of the quality of the negative examples. We plan to further explore alternative second-order negative sampling methods in our future work.
6.3 Appendix C: Dense Predictive Coding (DPC) t-SNE

To create the t-SNE plot from the embeddings in DPC [14], we took the pretrained weights of the 3D-Resnet-34 model learned on 224 × 224 pixel frames in the Kinetics400 dataset.

For every frame in the video that being visualised, we take a sequence of 25 frames with a temporal stride of 3. Thus the entire sequence spans 73 total frames (the starting frame plus 24 additional frames which are each three frames apart). From this sequence of 25, five non-overlapping blocks of five frames are created and input to the encoder function \( f(\cdot) \). The five output feature maps are subsequently input to the aggregator function \( g(\cdot) \) which outputs a single feature map with size \( 1 \times 7 \times 7 \times 256 \). Finally, the feature map is average-pooled to create a single feature vector of size \( 1 \times 256 \) which can then be further reduced via t-SNE for visualisation on a two-dimensional plot.

This is the same process used to create the t-SNE plot in DPC paper [14], but rather than only show one point per video we visualise the representations of all sequences of frames in the video to identify any temporal coherency that may arise from the training method in DPC. If there are \( T^i \) frames in the video \( V^i \) being visualised, the t-SNE plot will include \( T^i - 72 \) points.

Fig. 6: Network architecture for DPC, taken from [14].