Temporal Relational Reasoning in Videos

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Abstract

Temporal relational reasoning, the ability to link meaningful transformations of objects or entities over time, is a fundamental property of intelligent species. In this paper, we introduce an effective and interpretable network module, the Temporal Relation Network (TRN), designed to learn and reason about temporal dependencies between video frames at multiple time scales. We evaluate TRNequipped networks on activity recognition tasks using three recent video datasets - Something-Something, Jester, and Charades - which fundamentally depend on temporal relational reasoning. Our results demonstrate that the proposed TRN gives convolutional neural networks a remarkable capacity to discover temporal relations in videos. Through only sparsely sampled video frames, TRN-equipped networks can accurately predict human-object interactions in the Something-Something dataset and identify various human gestures on the Jester dataset with very competitive performance. TRN-equipped networks also outperform two-stream networks and 3D convolution networks in recognizing daily activities in the Charades dataset. Further analyses show that the models learn intuitive and interpretable visual common sense knowledge in videos¹.

1. Introduction

The ability to reason about the relations between entities over time is crucial for intelligent decision-making. Temporal relational reasoning allows intelligent species to analyze the current situation relative to the past and formulate hypotheses on what may happen next. For example (Fig.1), given two observations of an event, people can easily recognize the temporal relation between two states of the visual world and deduce what has happened between the two frames of a video².

Temporal relational reasoning is critical for activity recognition, forming the building blocks for describing the steps of an event. A single activity can consist of several temporal relations at both short-term and long-term



Figure 1. What takes place between two observations? (see answer below). Humans can easily infer the temporal relations and transformations between these observations, but this task remains difficult for neural networks.

timescales. For example, the activity of *sprinting* contains the long-term temporal relations of crouching at the starting blocks, running on track, and finishing at the end line, while also includes the short-term temporal relations of periodic hands and feet movement.

Activity recognition in videos has been one of the core topics in computer vision. However, it remains difficult due to the ambiguity of describing activities at appropriate timescales [21]. Many video datasets, such as UCF101 [24], Sport1M [11], and THUMOS [7], include many activities that can be recognized without reasoning about the long-term temporal relations: still frames and optical flow are sufficient to identify many of the labeled activities. Indeed, the classical two-stream Convolutional Neural Network [23] and the recent I3D Network [3], both based on frames and optical flow, perform activity recognition very well on these datasets.

However, convolutional neural networks still struggle in situations where data and observations are limited, or where the underlying structure is characterized by transformations and temporal relations, rather than the appearance of certain entities [17, 14]. It remains remarkably challenging for convolutional neural networks to reason about temporal relations and to anticipate what transformations are hap-

¹Code is available at http://relation.csail.mit.edu.

²Answer: Poking a stack of cans so it collapses; Tidying up a closet

pening to the observations. Fig.1 shows such examples. The networks are required to discover visual common sense knowledge over time beyond the appearance of objects in the frames and the optical flow.

In this work, we propose a simple and interpretable network module called Temporal Relation Network (TRN) that enables temporal relational reasoning in neural networks. This module is inspired by the relational network proposed in [17], but instead of modeling the spatial relations, TRN aims to describe the temporal relations between observations in videos. Thus, TRN can learn and discover possible temporal relations at multiple time scales. TRN is a general and extensible module that can be used in a plug-andplay fashion with any existing CNN architecture. We apply TRN-equipped networks on three recent video datasets (Something-Something [8], Jester [1], and Charades [22]), which are constructed for recognizing different types of activities such as human-object interactions and hand gestures, but all depend on temporal relational reasoning. The TRN-equipped networks achieve very competitive results even given only discrete RGB frames, bringing significant improvements over baselines. Thus TRN provides a practical solution for standard neural networks to solve activity recognition tasks using temporal relational reasoning.

1.1. Related Work

Convolutional Neural Networks for Activity Recog**nition**. Activity recognition in videos is a core problem in computer vision. With the rise of deep convolutional neural networks (CNNs) which achieve state-of-theart performance on image recognition tasks [13, 29], many works have looked into designing effective deep convolutional neural networks for activity recognition [11, 23, 4, 25, 28, 3]. For instance, various approaches of fusing RGB frames over the temporal dimension are explored on the Sport1M dataset [11]. Two stream CNNs with one stream of static images and the other stream of optical flows are proposed to fuse the information of object appearance and short-term motions [23]. 3D convolutional networks [25] use 3D convolution kernels to extract features from a sequence of dense RGB frames. Temporal Segment Networks sample frames and optical flow on different time segments to extract information for activity recognition [28]. A CNN+LSTM model, which uses a CNN to extract frame features and an LSTM to integrate features over time, is also used to recognize activities in videos [4]. Recently, I3D networks [3] use two stream CNNs with inflated 3D convolutions on both dense RGB and optical flow sequences to achieve state of the art performance on the Kinetics dataset [12]. There are several important issues with existing CNNs for action recognition: 1) The dependency on beforehand extraction of optical flow lowers the efficiency of the recognition system; 2) The 3D convolutions on sequences of dense frames are computationally expensive, given the redundancy in consecutive frames; 3) Since sequences of frames fed into the network are usually limited to 20 to 30 frames, it is difficult for the networks to learn long-term temporal relations among frames. To address these issues, the proposed Temporal Relation Network sparsely samples individual frames then learns their causal relations, which is much more efficient than sampling dense frames and convolving them. We show that TRN-equipped networks can efficiently capture temporal relations at multiple time scales and outperform dense frame-based networks using only sparsely sampled video frames.

Temporal Information in Activity Recognition. For activity recognition on many existing video datasets such as UCF101 [24], Sport1M [11], THUMOS [7], and Kinetics [12], the appearance of still frames and short-term motion such as optical flow are the most important information to identify the activities. Thus, activity recognition networks such as Two Stream network [23] and the I3D network [3] are tailored to capture these short-term dynamics of dense frames. Therefore, existing networks don't need to build temporal relational reasoning abilities. On the other hand, recently there are various video datasets collected via crowd-sourcing, which focus on sequential activity recognition: Something-Something dataset [8] is collected for generic human-object interaction. It has video classes such as 'Dropping something into something', 'Pushing something with something', and even 'Pretending to open something without actually opening it'. Jester dataset [1] is another recent video dataset for gesture recognition. Videos are recorded by crowd-source workers performing 27 kinds of gestures such as 'Thumbing up', 'Swiping Left', and 'Turning hand counterclockwise'. Charades dataset is also a high-level human activity dataset that collects videos by asking crowd workers to perform a series of home activities and then record themselves [22]. For recognizing the complex activities in these three datasets, it is crucial to integrate temporal relational reasoning into the networks. Besides, many previous works model the temporal structures of videos for action recognition and detection using bag of words, motion atoms, or action grammar [5, 16, 26, 6, 27]. Instead of designing temporal structures manually, we use a more generic structure to learn the temporal relations in end-to-end training. Thus it runs more efficiently to process videos in testing.

Relational Reasoning and Intuitive Physics. Recently, relational reasoning module has been proposed for visual question answering with super-human performance [17]. Our work is inspired by that work, but we focus on modeling the multi-scale temporal relations in videos. In the domain of robot self-supervised learning, many models have been proposed to learn the intuitive physics among frames. Given an initial state and a goal state, the inverse dynam-

ics model with reinforcement learning is used to infer the transformation between the object states [2]. Physical interaction and observations are also used to train deep neural networks [15]. Time contrast networks are used for self-supervised imitation learning of object manipulation from third-person video observation [18]. Our work aims to learn various temporal relations in videos in a supervised learning setting. The proposed TRN can be extended to self-supervised learning for robot object manipulation.

2. Temporal Relation Networks

In this section, we introduce the framework of Temporal Relation Networks. It is simple and can be easily plugged into any existing convolutional neural network architecture to enable temporal relational reasoning. In later experiments, we show that TRN-equipped networks discover interpretable visual common sense knowledge to recognize activities in videos.

2.1. Defining Temporal Relations

Inspired by the relational reasoning module for visual question answering [17], we define the pairwise temporal relation as a composite function below:

$$T_2(V) = h_\phi \left(\sum_{i < j} g_\theta(f_i, f_j) \right) \tag{1}$$

where the input is the video V with n selected ordered frames as $V=\{f_1,f_2,...,f_n\}$, where f_i is a representation of the i^{th} frame of the video, e.g., the output activation from some standard CNN. The functions h_{ϕ} and g_{θ} fuse features of different ordered frames. Here we simply use multilayer perceptrons (MLP) with parameters ϕ and θ respectively. For efficient computation, rather than adding all the combination pairs, we uniformly sample frames i and j and sort each pair.

We further extend the composite function of the 2-frame temporal relations to higher frame relations such as the 3-frame relation function below:

$$T_3(V) = h'_{\phi} \Big(\sum_{i < j < k} g'_{\theta}(f_i, f_j, f_k) \Big)$$
 (2)

where the sum is again over sets of frames i, j, k that have been uniformly sampled and sorted.

2.2. Multi-Scale Temporal Relations

To capture temporal relations at multiple time scales, we use the following composite function to accumulate frame relations at different scales:

$$MT_N(V) = T_2(V) + T_3(V)... + T_N(V)$$
 (3)

Each relation term T_d captures temporal relationships between d ordered frames. Each T_d has its own separate $h_\phi^{(d)}$ and $g_\theta^{(d)}$. Notice that for any given sample of d frames for each T_d , all the temporal relation functions are end-to-end differentiable, so they can all be trained together with the base CNN used to extract features for each video frame. The overall network framework is illustrated in Fig.2.

2.3. Efficient Training and Testing

When training a multi-scale temporal network, we could sample the sums by selecting different sets of d frames for each T_d term for a video. However, we use a sampling scheme that reduces computation significantly. First, we uniformly sample a set of N frames from the video, $V_N^* \subset V$, and we use V_N^* to calculate $T_N(V)$. Then, for each d < N, we choose k random subsamples of k frames k frames are used to compute the k-frame relations for each k frames. These are used to compute the k-frame relations to be sampled while evaluating the CNN on only k frames.

At testing time, we can use the TRN-equipped network in a moving window to process long videos. A feature queue is used to cache the extracted CNN features of equidistant frames sampled from the video, and those features are further combined into different relation tuples then fed into TRN to predict the activity. The CNN features are extracted from incoming frame only once then enqueued, thus making TRN-equipped networks very efficient to run in real-time on a desktop.

3. Experiments

We evaluate the TRN-equipped networks on a variety of activity recognition tasks. For recognizing activities that depend on temporal relational reasoning, TRN-equipped networks outperform a baseline network without a TRN by a large margin. We establish state-of-the-art results on the Something-Something dataset for human-interaction recognition [8] and on the Jester dataset for hand gesture recognition [1]. The TRN-equipped networks also obtain competitive results on activity classification in the Charades dataset [22], outperforming the Flow+RGB ensemble models [20, 22] using only sparsely sampled RGB frames.

The statistics of the three datasets Something-Something dataset [8], Jester dataset [1], and Charades dataset [22] are listed in Table 1. All three datasets are crowd-sourced, in which the videos are collected by asking the crowd-source workers to record themselves performing instructed activities. Unlike the Youtube-type videos in UCF101 and Kinetics, there is usually a clear start and end of each activity in the crowd-sourced video, emphasizing the importance of temporal relational reasoning.

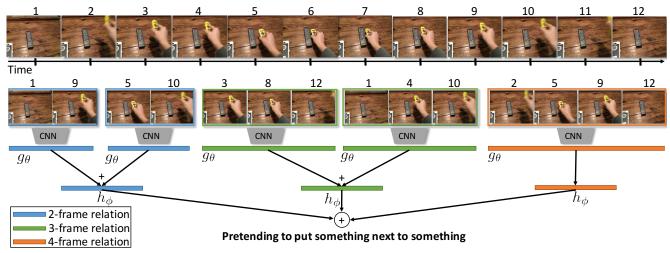


Figure 2. The illustration of Temporal Relation Networks. Representative frames of a video (shown above) are sampled and fed into different frame relation modules. Only a subset of the 2-frame, 3-frame, and 4-frame relations are shown, as there are higher frame relations included.

Table 1. Statistics of the datasets used in evaluating the TRNs.

Dataset	Classes	Videos	Type
Something	174	108,499	human-object interaction
Jester	27	148,092	human hand gesture
Charades	157	9,848	daily indoor activity

3.1. Network Architectures and Training

The networks used for extracting image features play an important factor in visual recognition tasks [19]. Features from deeper networks such as ResNet [9] usually perform better. Our goal here is to evaluate the effectiveness of the TRN module for temporal relational reasoning in videos. Thus, we fix the base network architecture to be the same throughout all the experiments and compare the performance of the CNN model with and without the proposed TRN modules.

We adopt Inception with Batch Normalization (BN-Inception) pretrained on ImageNet used in [10] because of its balance between accuracy and efficiency. We follow the training strategies of partial BN (freezing all the batch normalization layers except the first one) and dropout after global pooling as used in [28]. We keep the network architecture of the MultiScale TRN module and the training hyper-parameters the same for training models on all the three datasets. We set k=3 in the experiments as the number of accumulated relation triples in each relation module. g_{ϕ} is simply a two-layer MLP with 256 units per layer, while h_{ϕ} is a one-layer MLP with the unit number matching the class number. The CNN features for a given frame is the activation from the BN-Inception's global average pooling layer (before the final classification layer). Given the BN-Inception as the base CNN, the training can be finished in less than 24 hours for 100 training epochs on a single Nvidia Titan Xp GPU. In the Multi-Scale TRN, we include all the TRN modules from 2-frame TRN up to 8-frame TRN, as including higher frame TRNs brings marginal improvement and lowers the efficiency.

3.2. Results on Something-Something Dataset

Something-Something is a recent video dataset for human-object interaction recognition. There are 174 classes, some of the ambiguous activity categories are challenging, such as 'Tearing Something into two pieces' versus 'Tearing Something just a little bit', 'Turn something upside down' versus 'Pretending to turn something upside down'. We can see that the temporal relations and transformations of objects rather than the appearance of the objects characterize the activities in the dataset.

The results on the validation set are listed in Table 2, in which we compare the top1 and top5 accuracy for the base network trained on single frames randomly selected from each video, the base networks with various frame relation modules, and the multi-scale TRN-equipped network. Networks with TRNs outperform the single frame baseline by a large margin, while additional frames included in the relation bring further improvements. The Multi-Scale TRN with ten crop data augmentation achieves the best performance.

We submit the prediction of the MultiScale TRN on the test set to the official leaderboard³. At the submission time, our method tops the leaderboard using only discrete frames, as shown in Table 3.

³https://www.twentybn.com/datasets/something-something

Table 2. Results on the validation set of Something-Something Dataset. All the models use the center cropping of the equidistant frames in the video. Multi-scale TRN with 10-crop augmentation achieves the best performance.

model	Top1 acc.(%)	Top5 acc.
single frame	11.41	33.39
2-frame TRN	22.23	48.80
3-frame TRN	26.22	54.15
4-frame TRN	29.83	58.21
5-frame TRN	30.39	58.29
7-frame TRN	31.01	59.24
MultiScale TRN	33.01	61.27
MultiScale TRN (10-crop)	34.44	63.20

Table 3. Results on the test set of the Something-Something Dataset-V1. Comparison methods are from the official public leaderboard.

model	Top1 acc.(%)
Yana Hasson	25.55
Harrison.AI	26.38
I3D by [8]	27.23
Guillaume Berger	30.48
Besnet (Top1 on leaderboard)	31.66
MultiScale TRN	33.60

Table 4. Results on the validation set of the Jester Dataset-V1.

model	Top1 acc.(%)	Top5 acc.
single frame	63.60	92.44
2-frame TRN	75.65	94.40
MultiScale TRN	93.70	99.59
MultiScale TRN (10-crop)	95.31	99.86

Table 5. Results on the test set of Jester dataset-V1.			
model	Top1 acc.(%)		
20BN's Jester System	82.34		
VideoLSTM	85.86		
Guillaume Berger	93.87		
Ford's Gesture Recognition System	94.11		
Besnet (Top1 on leaderboard)	94.23		
MultiScale TRN	94.78		

3.3. Results on Jester and Charades

We further evaluate the TRN-equipped networks on the Jester dataset, which is a video dataset for hand gesture recognition with 27 classes. The results on the validation set of the Jester dataset are listed in Table 4. The result on the test set and comparison with the top methods in the official leaderboard ⁴ are listed in Table 5. MultiScale TRN again achieves the state-of-the-art performance with close to 95% accuracy.

Table 6. Results on Charades Activity Classification.

Approach	mAP	Approach	mAP
Random	5.9	C3D	10.9
AlexNet	11.3	IDT	17.2
Two-Stream	14.3	AsycTempField	22.4
MultiScale TRN	25.2		

We evaluate the MultiScale TRN on the recent Charades dataset for daily activity recognition. The results are listed in Table 6. Our method outperforms various methods such as 2-stream networks and C3D [22], and the recent Asynchronous Temporal Field (AsycTempField) method [20].

The qualitative prediction results of the Multi-Scale TRN on the three datasets are shown in Figure 3. The examples in Figure 3 demonstrate that the TRN model is capable of correctly identifying actions for which the overall temporal ordering of frames is essential for a successful prediction. For example, the turning hand counterclockwise category would assume a different class label when shown in reverse. Moreover, the successful prediction of categories in which an individual *pretends* to carry out an action (e.g. 'pretending to put something into something' as shown in the second row) suggests that the network can capture temporal relations at multiple scales, where the ordering of several lower-level actions contained in short segments conveys crucial semantic information about the overall activity class.

This outstanding performance shows the effectiveness of the TRN for temporal relational reasoning and its strong generalization ability across different datasets.

3.4. Interpreting Visual Common Sense Knowledge inside the TRN

One of the distinct properties of the proposed TRNs compared to previous video classification networks such as C3D [25] and I3D [3] is that TRN has more interpretable structure. In this section, we have a more in-depth analysis to interpret the visual common sense knowledge learned by the TRNs through solving these temporal reasoning tasks. We explore the following four parts:

Representative frames of a video voted by the TRN to recognize an activity. Intuitively, a human observer can capture the essence of an action by selecting a small collection of representative frames. Does the same hold true for models trained to recognize the activity? To obtain a sequence of representative frames for each TRN, we first compute the features of the equidistant frames from a video, then randomly combine them to generate different frame relation tuples and pass them into the TRNs. Finally we rank the relation tuples using the responses of different TRNs. Figure 4 shows the top representative frames voted by different TRNs to recognize an activity in the same video. We can see that the TRNs learn the temporal relations that characterize an activity. For comparatively simple actions, a single frame is sufficient to establish some degree of con-

⁴https://www.twentybn.com/datasets/jester

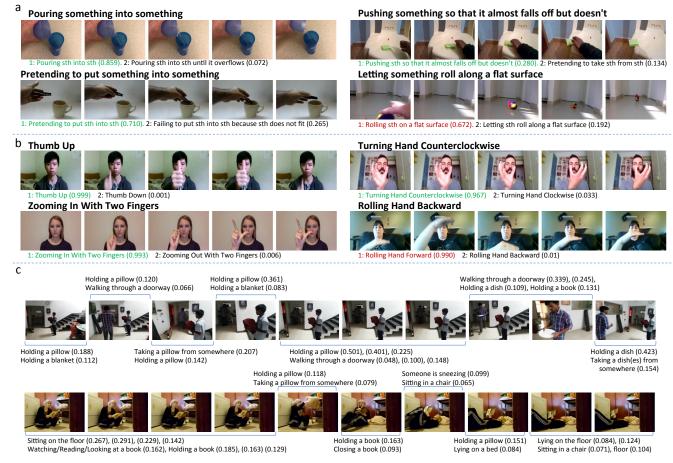


Figure 3. Prediction examples on a) Something-Something, b) Jester, and c) Charades. For each example drawn from Something-Something and Jester, the top two predictions and corresponding class probabilities accompany five uniformly-sampled frames with green text indicating a correct top1 prediction and red indicating an incorrect one. Due to the extended length of the videos in Charades, each plotted image is the middle frame of a 10-frame sequence sampled evenly over a time interval, over which the top two class predictions are shown.

fidence in the correct action, but is vulnerable to mistakes when a transformation is present. 2-frame TRN picks up the two frames that best describe the transformation. Meanwhile, for more difficult activity categories such as 'Pretending to poke something', two frames are not sufficient information for even a human observer to differentiate. Similarly, the network needs additional frames in the TRNs to correctly recognize the behavior.

Thus the progression of representative frames and their corresponding class predictions inform us about how temporal relations may help the model reason about more complex behavior. One particular example is the last video in Figure 4: The action's context given by a single frame - a hand close to a book - is enough to narrow down the top prediction to a qualitatively plausible action, unfolding something. A similar, two-frame relation marginally increases the probability the initial prediction, although these two frames would not be sufficient for even human observers to make the correct prediction. Now, the three frame-relation begins to highlight a pattern characteristic to Something-

Somethings set of *pretending* categories: the initial frames closely resemble a certain action, but the later frames are inconsistent with the completion of that action as if it never happened. This relation helps the model to adjust its prediction to the correct class. Finally, the upward motion of the individuals hand in the third frame of the 4-frame relation further increases the discordance between the *anticipated* and *observed* final state of the scene; a motion resembling the action appeared to take place with no effect on the object, thus, solidifying confidence in the correct class prediction.

Importance of temporal order for activity recognition. To verify the importance of the temporal order of

frames for activity recognition, we conduct an experiment to compare the scenario with input frames in temporal order and in shuffled order when training the TRNs, as shown in Figure 5. For training the shuffled TRNs, we randomly shuffle the frames in the relation modules. The significant difference on the Something-Something dataset shows the importance of the temporal order in the activity recog-

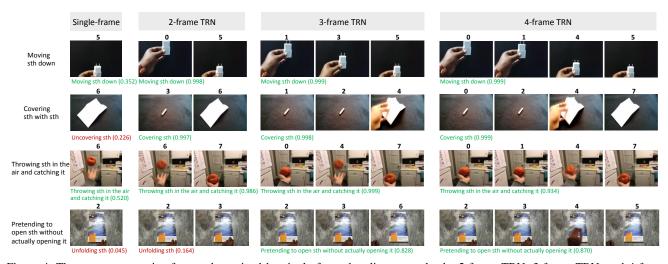


Figure 4. The top representative frames determined by single frame baseline network, the 2-frame TRN, 3-frame TRN, and 4-frame TRN. TRNs learn to capture the essence of an activity only given a limited number of frames. Videos are from the validation set of the Something-Something dataset

nition. More interestingly, we repeat the same experiment on the UCF101 dataset [24] and observe no difference between the ordered frames and shuffled frames. That shows activity recognition for the Youtube-type videos in UCF101 don't necessarily require the temporal reasoning ability since there are not so many casual relations associated with an already on-going activity.

To further investigate how temporal ordering influences activity recognition in TRN, we examine and plot the categories that show the largest differences in the class accuracy between ordered and shuffled inputs drawn from the Something-Something dataset, in Figure 6. In general, actions with strong 'directionality and large, one-way movements, such as 'Moving something down', appear to benefit the most from preserving the correct temporal ordering. This observation aligns with the idea that the disruption of continuous motion and a potential consequence of shuffling video frames, would likely confuse a human observer, as it would go against our intuitive notions of physics.

Interestingly, the penalty for shuffling frames of relatively static actions is less severe if penalizing at all in some cases, with several categories marginally benefiting from shuffled inputs, as observed with the category 'putting something that can't roll onto a slanted surface so it stays where it is'. Here, simply learning the coincidence of frames rather than temporal transformations may be sufficient for the model to differentiate between similar activities and make the correct prediction.

Particularly in challenging ambiguous cases, for example 'Pretending to throw something' where the release point is partially or completely obscured from view, disrupting a strong 'sense of motion' may bias model predictions away from the likely alternative, 'throwing something', frequently but incorrectly selected by the ordered model, thus

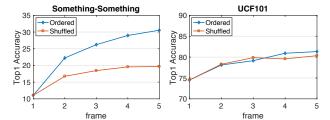


Figure 5. Accuracy obtained by different frame TRNs using ordered frames and shuffled frames, on Something-Something and UCF101 dataset respectively. On Something-Something, the temporal order is critical for recognizing the activity. In contrast, recognizing activities in UCF101 does not necessarily require temporal relational reasoning.

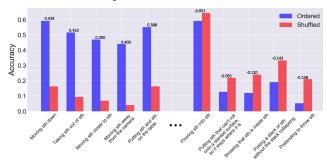


Figure 6. The top 5 action categories that exhibited the largest gain and the least gain (negative) respectively between ordered and shuffled frames as inputs (difference value is labeled above). Actions with strong directional motion appear to suffer most from shuffled inputs. In most cases, shuffling is least detrimental to actions with comparatively subtle movements.

giving rise to a curious difference in accuracy for that action.

t-SNE visualization of activity similarity. Figure 7 shows the t-SNE visualization for embedding the high-level

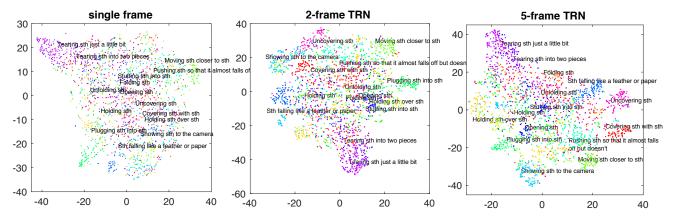


Figure 7. t-SNE plot of the video samples of the 15 classes using the deep features from the single-frame baseline, 2-frame TRN, and 5-frame TRN. Higher frame TRN can better differentiate activities in Something-Something dataset (better view in color version with zooming in).



Figure 8. Anticipating and forecasting activity when only given the first 25% frames. The first 25% of each video, represented by the first frame shown in the left column, is used to generate the top 3 anticipated forecasts and corresponding probabilities listed in the middle column. The ground truth label is highlighted by a blue arrow which points to the last frame of the video (not observed by the network) on the right.

features from the single frame baseline, the 3-frame TRN, and the 5-frame TRN, for the videos of the 15 most frequent activity classes in the validation set. We can see that the features from 2-frame and 5-frame TRNs can better differentiate activity categories. We also observe the similarity among categories in the visualization map. For example, 'Tearing something into two pieces' is very similar to 'Tearing something just a little bit', and the categories 'Folding something', 'Unfolding something', 'Holding something', 'Holding something' are clustered together.

Anticipating activities. Anticipating and forecasting activities before they happen or fully happen is a challenging

Table 7. Anticipating activities using the MultiScale TRN on Something-Something and Jester dataset. Only the first 25% and 50% of frames are given to the TRN to predict activities. Here the baseline is the model trained on single frames.

	Something		Jester	Jester	
Data	baseline	TRN	baseline TRI	V	
first 25%	9.08	11.14	27.25 34.2	3	
first 50%	10.10	19.10	41.43 78.4	2	
full	11.41	33.01	63.60 93.7	0	

yet less explored problem in activity recognition. Here we evaluate our TRN model on anticipating activity when given only the first 25% and 50% of the frames in each validation video. Results are shown in Table 7. For comparison, we also include the single frame baseline. We see that TRN can use the learned temporal relations to anticipate activity. The performance increases as more ordered frames are received. Figure 8 shows some examples of anticipating activities using only first 25% frames of a video. A qualitative review of these examples reveals that model predictions on only initial frames do serve as very reasonable forecasts despite being given task with a high degree of uncertainty even for human observers.

4. Conclusion

We proposed a simple and interpretable network module called Temporal Relation Network (TRN) to enable temporal relational reasoning in neural networks for videos. We evaluated the proposed TRN on several recent datasets and established competitive results using only discrete frames. Finally, we have shown that TRN modules discover visual common sense knowledge in videos.

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