Temporal Aggregate Representations for Long Term Video Understanding

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Abstract. Future prediction requires reasoning from current and past observations and raises several fundamental questions. How much past information is necessary? What is a reasonable temporal scale to process the past? How much semantic abstraction is required? We address all of these questions with a flexible multi-granular temporal aggregation framework. We show that it is possible to achieve state-of-the-art results in both next action and dense anticipation using simple techniques such as max pooling and attention. To demonstrate the anticipation capabilities of our model, we conduct experiments on the Breakfast Actions, 50Salads and EPIC-Kitchens datasets where we achieve state-of-the-art or comparable results. We also show that our model can be used for temporal video segmentation and action recognition with minimal modifications.

Keywords: action anticipation, temporal aggregation, video understanding

1 Introduction

We tackle long-term video understanding, specifically anticipating not-yet-observed but upcoming actions. When developing intelligent systems, one needs not only to recognize what is currently taking place – but also predict what will happen next. Anticipating human actions is essential for many applications such as smart surveillance, autonomous driving, assistive robotics, and other human-computer interfaces.

While action anticipation is a niche (albeit rapidly growing) area, the key issues that arise are germane to long-term video understanding as a whole. How should temporal or sequential relationships be modelled? What temporal extent of information and context needs to be processed? At what temporal scale should they be derived and how much semantic abstraction is required? The answers to these questions are not only entangled with each other but also depend very much on the videos being analyzed. Here, one needs to distinguish between clipped actions, e.g. of UCF101 \cite{UCF101}, versus the multiple actions in long video streams, e.g. of the Breakfast Actions \cite{BreakfastActions}. In the former, the actions and video clips are on the order of a few seconds, while in the latter, it is several minutes. As such, temporal modelling is usually not necessary for simple action recognition \cite{简单动作识别}, but more relevant for understanding complex activities \cite{复杂活动理解}.

Temporal models that are built into the architecture \cite{时间模型} are generally favoured because they allow frameworks to be learned end-to-end. However, this means that the architecture also dictates the temporal extent that can be accounted for. This tends to be short, either due to difficulties in memory retention or model size. As a result, the context for anticipation can only be drawn from a limited extent of recent observations, usually on the order of seconds \cite{上下文}. This in turn limits the temporal horizon and granularity of the prediction.
One way to ease the computational burden, especially under longer temporal extents, is to use higher-level but more compact feature abstractions, e.g. by using already detected objects and people [44] or even sub-activity labels [1,16] based on the outputs of temporal video segmentation algorithms [31]. Such an approach places a strong semantic load on the initial task of segmentation and is often difficult to train end-to-end. Furthermore, since labelling and segmenting actions from video are difficult tasks, their errors may propagate onwards when anticipating future actions.

Motivated by these questions of temporal modelling, extent, scaling, and level of semantic abstraction, we propose a general framework for encoding long-term video. We aim for flexibility in frame input, i.e. ranging from low-level visual features to high-level semantic labels, and the ability to meaningfully integrate recent observations with long-term context, all in a computationally efficient way.

To do so, we split video streams into snippets of equal length and max-pool the frame features within the snippets. We then create ensembles of multi-scale feature representations that are aggregated bottom-up based on scaling and temporal extent. Temporal aggregation [18] is a form of summarization used in temporal database systems. Our framework is loosely analogous as it summarizes the past observations through aggregation, so we name it “temporal aggregates”. Temporal aggregate features can be applied to several video understanding tasks; in addition to action anticipation, it can also be used for recognition and temporal segmentation.

Our model is similar in spirit to the long-term feature banks of Wu et al. [44] in that we couple the recent with the long-term past using attention. However, one key difference is that we work with an ensemble of multiple scalings and granularities, whereas Wu et al. work at a single (frame-level) granularity. As such, we can handle long streams of videos that can span tens of minutes, while they are only able to work on short video clips. Furthermore, their method requires a preliminary step of object and person detection while we can work directly on frame-wise features, making our inputs much simpler. We summarize our main contributions as follows:

- We propose a simple and flexible end-to-end framework of multi-scale temporal aggregates for long-term videos by relating recent observations to long-term past.
- Our proposed temporal model can be used for video understanding tasks such as action recognition, anticipation and temporal video segmentation with minimal modifications and is able to achieve competitive results.
- Our model has minimal constraints regarding the type of anticipation (dense or next action), type of the dataset (instructional or daily activities), and type of input features (visual features or frame-level labels).
- We show that our method either outperforms or is on par with the state of the art for anticipation, recognition and segmentation with experiments conducted on three datasets: Breakfast Actions [20], 50Salads [36] and EPIC-Kitchens [5].

2 Related Works

Action recognition has advanced significantly with deep networks in recent years. Notable works include two stream networks [33,42], 3D convolutional networks [38,46,3], and recurrent neural networks [7,47]. These methods have been designed to encode short clips of a few seconds and are typically applied to the classification of trimmed
videos containing a single action such as those found in the UCF [34] and Kinetics
[14] datasets. In contrast, in this paper, we are working with long untrimmed sequences
of complex activities. Such long videos are not simply a composition of independent
short actions, as the composing segments are related to each other with sequence dy-
namics. Various models for complex activity understanding have been addressed be-
fore [20,6,8,32], these approaches are designed to work on instructional videos by ex-
PLICITLY modelling their sequence dynamics. These models are not flexible enough to be
extended to daily activities with loose orderings. Moreover, when only partial observa-
tions are provided, e.g. for anticipation, these models cannot be trained end-to-end.

**Action anticipation**, a fast-growing field, aims to forecast actions before they occur. We
distinguish between immediate anticipation of next action label and dense anticipation.
Prior works in immediate anticipation were initially limited to movement primitives
like reaching or moving [19] or interactions such as hugging and hand-shaking [40].
[26] presents a model for predicting both the next action and its starting position. [5]
presents a large daily activities dataset, along with a challenge for anticipating the next
action one second before occurrence. [28] proposes direct next action anticipation from
recent observations. Recently, [10] proposed using an LSTM to summarize the past,
and another LSTM for future prediction. All these works assume current or near-past
information, whereas we make use of long-term past for anticipation.

**Dense anticipation** predicts actions multiple steps into the future. Previous methods [1,16]
to date have all relied on having already segmented temporal observations. Different
than these, our model can perform dense anticipation in a single stage without any pre-
segmented nor labelled inputs. Our model is the first and only one that can perform
dense anticipation in an end-to-end manner on long-term videos.

The role of motion and temporal dynamics has been well-explored for video under-
standing, though the focus has been on short video clips [24,7,3,13,27]. Some works
were able to use longer-term temporal contexts in short videos using pre-computed fea-
tures [23,37]. Recently, Wu et al. [44] proposed integrating long-term features with 3D
CNNs for action recognition in short videos and showed the importance of incorporat-
ing temporal context for action recognition. Recently Feichtenhofer et al. [9] proposed
SlowFast networks, which similar to our model, encode time-wise multi-scale repre-
sentations. Using a two-stream architecture working on differently sampled versions of
the video, they aim to capture slow spatial semantics and fast motion features which
are successively concatenated. In contrast, our multiscale spanning past is built on stan-
dard features extracted at a fixed sampling rate. Our spanning features of all scales are
processed w.r.t. all recent scales via an attention mechanism. Most importantly, these
approaches are limited to short videos and cannot be extended to minute long videos
due to computational constraints. Our temporal modeling enables encoding minute-long
videos, while being flexible enough to be applied to any dataset for several tasks.

3 **Representations**

We begin by introducing the representations which are inputs to the building blocks of
our framework, see Fig. 1. We had two rationales when designing our network. First,
the coupling blocks relate recent observations to long-range past, since some actions
directly determine what future actions can or cannot be. Second, to represent recent and
long-term past at various granularities, we pool snippets over multiple scales.
input video sequence

next action prediction
dense anticipation

spanning past

recent past

max-pooling

Fig. 1. Model overview: In this example we use 3 scales for computing the “spanning past” snippet features $S_{K_1}, S_{K_2}, S_{K_3}$, and 2 starting points to compute the “recent past” snippet features, $R_{i_1}, R_{i_2}$, by max-pooling over the frame features in each snippet. Each recent snippet is coupled with all the spanning snippets in our Temporal Aggregation Block (TAB). An ensemble of TAB outputs is used for dense or next action anticipation. Best viewed in color.

3.1 Pooling

For a video of length $T$, we denote the feature representation of a single video frame indexed at time $t$ as $f_t \in \mathbb{R}^D, 1 \leq t \leq T$. $f_t$ can be derived from low-level features, such as IDT [41] or I3D [3], or high-level abstractions, such as sub-activity labels derived from segmentation algorithms. To reduce computational load, we work at a snippet-level and define a snippet feature $F_{ij;K}$ as the concatenation of max-pooled features from $K$ snippets, where snippets are partitioned consecutively from frames $i$ to $j$:

$$F_{ij;K} = [F_{i,i+k}, F_{i+k+1,i+2k}, ..., F_{j-k+1,j}],$$

where

$$(F_{p,q})_d = \max_{p \leq t \leq q} \{f_t\}_d, 1 \leq d \leq D, \quad k = (j - i)/K.$$  

Here, $F_{p,q}$ indicates the maximum over each dimension $d$ of the frame features in a given snippet between frames $p$ and $q$, though it can be substituted with other alternatives. In the literature, methods representing snippets or segments of frames range from simple sampling and pooling strategies to more complex representations such as learned pooling [25,27] and LSTMs [29]. Especially for long snippets, it is often assumed that a learned representation is necessary [11,22], though their effectiveness over simple pooling is still controversial [42]. The learning of novel temporal pooling approaches goes beyond the scope of this work and is an orthogonal line of development. In this paper, we verify established methods (see Sec. 5.2) and find that a simple max-pooling is surprisingly effective and sufficient.

3.2 Recent vs. Spanning Representations

Based on different start and end frames $i$ and $j$ and number of snippets $K$, we define two types of snippet features: ‘recent’ features $\{R\}$ from recent observations and “spanning” features $\{S\}$ drawn from the entire video. The recent snippets cover the couple of seconds (or up to a minute, depending on the temporal granularity) before the current time point, while spanning snippets refer to the long-term past and may last up to ten minutes. For “recent” snippets, the end frame $j$ is fixed to the current time point $t$ and the number of snippets is fixed to $K_R$. Recent snippet features $R$ can be defined
For the recent past, it is sufficient to keep the number of snippets \(K\) as a feature bank of snippet features with different start frames \(i\), i.e.
\[
\mathcal{R} = \{F_{i_1:t;K_R}, F_{i_2:t;K_R}, \ldots, F_{i_{R};t;K_R}\} = \{R_{i_1}, R_{i_2}, \ldots, R_{i_{R}}\},
\]
where \(R_i \in \mathbb{R}^{D \times K_R}\) is a shorthand to denote \(F_{i_t;K_R}\), since endpoint \(t\) and number of snippets \(K_R\) are fixed. In Fig. 1 we use two starting points to compute the “recent past” snippet features and represent each with \(K_R = 3\) number of snippets (\(\square\) & \(\text{■}\)).

For “spanning” snippets, \(i\) and \(j\) are fixed to the start of the video and current time point, i.e. \(i = 0, j = t\). Spanning snippet features \(S\) are defined as a feature bank of snippet features with varying number of snippets \(K\), i.e.
\[
\mathcal{S} = \{F_{0:t;K_1}, F_{0:t;K_2}, \ldots, F_{0:t;K_3}\} = \{S_{K_1}, S_{K_2}, \ldots, S_{K_3}\},
\]
where \(S_K \in \mathbb{R}^{D \times K}\) is a shorthand for \(F_{0,t;K}\). In Fig. 1 we use three scales to compute the “spanning past” snippet features with \(K = \{7, 5, 3\}\) (\(\text{■} \text{■} \text{■} \text{■}\) & \(\text{■} \text{■} \text{■}\)).

Key to both types of representations is the ensemble of snippet features from multiple scales. We achieve this by varying the number of snippets \(K\) for the spanning past. For the recent past, it is sufficient to keep the number of snippets \(K_R\) fixed, and vary only the start point \(i\), due to redundancy between \(\mathcal{R}\) and \(\mathcal{S}\) for the snippets that overlap. For our experiments, we work with snippets ranging from seconds to several minutes.

### 4 Framework

In Fig. 2 we present an overview of the components used in our framework, which we build in a bottom up manner, starting with the recent and spanning features \(\mathcal{R}\) and \(\mathcal{S}\), which are coupled with non-local blocks (NLB) (Sec. 4.1) within coupling blocks (CB) (Sec. 4.2). The outputs of the CBs from different scales are then aggregated inside temporal aggregation blocks (TAB) (Sec. 4.3). Outputs of different TABs can then be chained together for either next action anticipation or dense anticipation (Secs. 5.3, 5.5).

#### 4.1 Non-Local Blocks (NLB)

We apply non-local operations to capture relationships amongst the spanning snippets and between spanning and recent snippets. Non-local blocks [43] are a flexible way to relate features independently from their temporal distance and thus capture long-range dependencies. We use the modified non-local block from [44], which adds layer...
normalization [2] and dropout [35] to the original one in [42]. Fig. 2 (left) visualizes the architecture of the block, the operation of which we denote as NLB(·, ·).

4.2 Coupling Block (CB)
Based on the NLB, we define attention-reweighted spanning and recent outputs as:

\[ S'_{K} = NLB(S_K, S_K) \quad \text{and} \quad R'_{i,K} = NLB(S'_{K}, R_i). \]  

(4)

The coupling is done by concatenating \( R'_{i,K} \) with either \( R_i \) or \( S'_{K} \) and passed through linear layers. This results in the fixed-length representations \( R''_{i,K} \) and \( S''_{i,K} \), where \( i \) is the starting point of the recent snippet and \( K \) is the scale of the spanning snippet.

4.3 Temporal Aggregation Block (TAB)
The final representation for recent and spanning past is computed by aggregating outputs from multiple CBs. For the same recent starting point \( i \), we concatenate \( R''_{i,K_1}, ..., R''_{i,K_S} \) for all spanning scales and pass the concatenation through a linear layer to compute \( R'''_{i} \). The final spanning past representation \( S'''_{i} \) is a max over all \( S''_{i,K_1}, ..., S''_{i,K_S} \).

We empirically find that taking the max outperforms other alternatives like linear layers and/or concatenation for the spanning past (see 5.2).

TAB outputs, by varying recent starting points \( \{i\} \) and scales of spanning snippets \( \{K\} \), are multi-granular video representations that aggregate and encode both the recent and long-term past. We name these temporal aggregate representations. Fig.1 shows an example with 2 recent starting points and 3 spanning scales. Temporal aggregate representations are generic and can be applied in various video understanding tasks (see Sec. 4.4) from long streams of video.

4.4 Prediction Model

Classification: For single-label classification tasks such as next action anticipation, temporal aggregate representations can be used directly with a classification layer (linear + softmax). A cross-entropy loss based on ground truth labels \( Y \) can be applied to the predictions \( \hat{Y} \), where \( Y \) is either the current action label for recognition, or the next action label for next action prediction, see Fig. 3.

When the individual actions compose a complex activity (e.g. “take bowl” and “pour milk” as part of “making cereal” in Breakfast [20]), we can add an additional loss based on the complex activity label \( Z \). We postulate that predicting \( Z \) as an auxiliary task will boost the performance. For this we concatenate \( S''_{i_1}, ..., S''_{i_R} \) from all TABs and again pass them through a classification layer to obtain \( \hat{Z} \). Our final loss formulation is the sum of the cross entropies over the action and complex activity labels respectively:

\[ L_{cl} = L_{comp} + L_{action} = - \sum_{n=1}^{N_Z} Z_n \log(\hat{Z})_n - \sum_{r=1}^{R} \sum_{n=1}^{N_Y} Y_n \log(\hat{Y}_r)_n, \]  

(5)

where \( i_r \) is one of the \( R \) recent starting points, and \( N_Y \) and \( N_Z \) are the total number of actions and complex activity classes respectively. During inference, the predicted scores are summed for a final prediction, i.e. \( \hat{Y} = \max_n (\sum_{r=1}^{R} \hat{Y}_r)_n. \)
We also frame sequence segmentation as a classification task. Here the task is predicting frame-level action labels of complex activity videos. We generate multiple sliding windows with start and end times \( t_s \) and \( t_e \). Our goal is to classify each window into an action using the loss in Eq. 5.

**Sequence prediction:** The dense anticipation task predicts frame-wise action labels of the entire future sequence. Others [1] have formulated this task as predicting future segment labels and regressing their durations. We adopt a similar approach, but also estimate the duration via classification. We discretize the sequence duration into \( N_D \) intervals and represent durations as one-hot encodings \( D \in \{0, 1\}^{N_D} \).

For dense predictions, we perform multi-step estimates, distinguishing between the current action and its duration versus future actions and durations. We first estimate the current action and complex activity label, as described in Eq. 6. The current duration \( D \) is then estimated via a classification layer applied to the concatenation of recent temporal aggregates \( R''_{i_1}, ..., R''_{i_R} \).

For future actions, we concatenate all recent and spanning temporal aggregates \( R''_{i_1}, ..., R''_{i_R} \) and \( S''_{i_1}, ..., S''_{i_R} \), as well as the classification layer outputs \( \hat{Y}_{i_1}, ..., \hat{Y}_{i_R} \), and pass the concatenation through a linear layer before feeding the output to a one-layer LSTM. The LSTM consecutively predicts \( M \) future action labels and their durations. For this, at each iteration \( m \), the LSTM predicts an action vector \( \hat{Y}_m \) and a duration vector \( \hat{L}_m \). At each step the future action and its length are combined and fed to the LSTM to predict the next future action and length (see Fig. 3).

We formulate the dense anticipation loss as the sum of the cross-entropies over the current action, its duration, future actions and durations, and task labels respectively:

\[
L_{\text{dense}} = L_{\text{cl}} - \sum_{n=1}^{N_D} D_n \log(\hat{D}_n) - \frac{1}{M} \sum_{m=1}^{M} \left( \sum_{n=1}^{N_Y} Y^m_n \log(\hat{Y}^m_n) + \sum_{n=1}^{N_D} D^m_n \log(\hat{D}^m_n) \right) \tag{6}
\]

During inference we sum the predicted scores (post soft-max) for all starting points \( i_r \) to predict the current action as \( \max_n(\sum_{r=1}^{R} \hat{Y}_{i_r})_n \). The LSTM is then applied recursively to predict subsequent actions and durations by feeding previous predictions until the full sequence length is reached.

### 4.5 Implementation Details

We train our model using the Adam optimizer [17] with batch size 10, learning rate \( 10^{-4} \) and dropout rate 0.3. We train for 45 epochs and decrease the learning rate by a factor of 10 every 10th epoch. We use 1024 dimensions for all non-classification linear layers. The LSTMs in dense anticipation have one layer and 512 hidden units.
5 Experiments

5.1 Datasets and Features

We experiment on three complex activity datasets: Breakfast Actions [20], 50Salads [36] and EPIC-Kitchens [5]. The sequences in each reflect realistic durations and orderings of actions, which is crucial for real-world deployment of anticipation models. Relevant statistics about the datasets are given in Table 1. One notable difference between these datasets is the label granularity; it is very fine-grained for EPIC, hence their 2513 action classes, versus the coarser 48 and 17 actions of Breakfast and 50Salads. As a result, the median action segment duration is 8-16x shorter.

Feature-wise, we use Fisher vectors precomputed from [1] and I3D [3] for Breakfast, Fisher vectors for 50Salads, and appearance, optical flow and object-based features as provided by [10] for EPIC-Kitchens. Results for Breakfast and 50Salads are averaged over the predefined 4 and 5 splits respectively. Since 50Salads has only a single complex activity (making salad) we omit complex activity prediction for it. For EPIC-Kitchens, we report results on the test set of the Anticipation Challenge. 

Evaluation Measures are class accuracy (Acc.) for next action prediction and mean over frames accuracy [1] for dense prediction. For EPIC-Kitchens we report Top-1 and Top-5 accuracies to be consistent with [28,10].

Parameters: The spanning scales \( \{ K \} \), recent scale \( K_R \) and recent starting points \( \{ i \} \) are given in Table 1. We cross validated the parameters on different splits of 50Salads and Breakfast and used a validation set for selecting EPIC-Kitchens parameters. The starting points for EPIC-Kitchens are much smaller than the others due to its fine label granularity. We use intervals of 5 and 20 seconds for Breakfast and 50Salads for discretizing the durations in dense anticipation.

| Dataset            | video duration median, mean ±std | # classes | # segments | \( \{ i \} \) (in seconds) | \( K_R \) | \( \{ K \} \) |
|--------------------|----------------------------------|-----------|------------|-----------------------------|----------|---------|
| Breakfast(@15fps)  | 15.1s, 26.6s ±36.8               | 48        | 11.3K      | \( \{ t−10, t−20, t−30 \} \) | 5        | \{10,15,20\} |
| 50Salads(@30fps)   | 29.7s, 38.4s ±31.5               | 17        | 0.9K       | \( \{ t−5, t−10, t−15 \} \) | 5        | \{5,10,15\}  |
| EPIC(@60fps)       | 1.9s, 3.7s ±5.6                  | 2513      | 28.5K      | \( \{ t−2, t−1.5, t−1, t−0.5 \} \) | 2        | \{2,3,5\}   |

Table 1. Dataset details and our respective model parameters.

5.2 Component validation

The design choices for our framework are inspired by state-of-the-art trends such as attention [43,44] and careful experimentation. We verify each component’s utility via a series of ablation studies which are summarized in Table 2. As our main motivation was to develop a representation for long video streams to perform anticipation, we experiment on the Breakfast Actions dataset for next action anticipation. Our full model gets a performance of 40.1% accuracy averaged over actions.

Video Representation: Several short-term spatio-temporal feature representations have been proposed for video, e.g. 3D convolutions [38], or combining CNNs and RNNs for sequences [47,7]. For long video streams, it becomes difficult to work with all the raw features. Selecting representative features can be as simple as sub-sampling the frames, as e.g. in the SlowFast Networks [9,45], or pooling [42], to more complex RNNs [47]. Current findings in the literature are not in agreement. Some propose learned strategies [27,22], while others advocate pooling [42]. Our experiments align with the latter,
showing that max-pooling is superior to both sampling (+8%) and the GRU (+2.2%) or bi-directional LSTM [4] (+1.4%). The performance of GRU and bi-LSTM are comparable to those of min- and average-pooling, but significantly increases the training and inference time. Of the variants of pooling, max-pooling works best. This is in contradiction to the findings of [42]. We attribute this to the fact that we pool over minutes-long snippets and it is likely that mean-pooling smooths away salient features that are otherwise preserved by max-pooling. The minimum and maximum snippet durations, over which we apply pooling, are 0.4s and 115.3s for 50Salads, 0.1s and 64.5s for Breakfast, and 1.2s and 3.0s for EPIC. Note that we conducted a similar pooling ablation between mean- and max-pooling on EPIC-Kitchens, where we observed a 1.3% increase with max-pooling.

**Recent and Spanning Representations:** In our ablations, unless otherwise stated, an ensemble of 3 spanning scales $K = \{10, 15, 20\}$ and 3 recent starting points $i = \{t - 10, t - 20, t - 30\}$ are used. Table 2 (a) compares single starting points for the recent snippet features versus an ensemble. With a single starting point, points too near to and too far from the current time decrease the performance. The worst individual result is with $i_4 = 0$, i.e. using the entire sequence; the peak is at $i_2 = t - 20$, though an ensemble is still best. In Table 2 (b), we show the influence of spanning snippet scales. These scales determine the temporal snippet granularity; individually, results are not significantly different across the scales, but as we begin to aggregate an ensemble, the results improve. The ensemble with 4 scales is best but only marginally better than 3, at the expense of a larger network, so we choose $K = \{10, 15, 20\}$. In Table 2 (c), we show the influence of recent snippet scales. We find $K_R = 5$ performs best.

**Coupling Blocks:** Previous studies on simple video understanding have shown the benefits of using features from both the recent and long-term past [23,44]. A naïve way to use both recent and long-term features is to simply concatenate the two. However, combining the two in a learned way, e.g. via attention, is superior (+6.4%). To incorporate attention, we apply Non-Local Blocks (NLBs) [43], which is an adaptation of the attention mechanism that is popularly used in machine translation.

Different than the simple feature vector concatenations in SlowFast, we couple the max-pooling outputs in our Coupling Blocks (CBs) which are very essential components of our model. When we replace our CBs with concatenation + linear layer, we...
observe a drop of 6.7%. When we do not use coupling but separately pass the $R_i$ and $S_K$ through concatenation + linear layer, we observe a drop of 7.5%. We find that coupling the recent $R_i$ and long term $S_K$ information is critical. Coupling only recent information (-5.9%) does not keep sufficient context, whereas coupling only long-term past (-5%) does not leave sufficient representation for the more relevant recent aspects. The Temporal Aggregation Blocks (TAB) are the most critical component. Omitting them and directly classifying a single CB’s outputs significantly decreases accuracy (-8%). The strength of the TAB comes from using an ensemble of coupling blocks as input (single, -2.1%) and using the TABs in an ensemble (single, -2.4%).

Additional ablations: When we omit the auxiliary complex activity prediction, i.e. removing the $Z$ term from Eq. 6 (“no $Z$”), we observe a slight performance drop of 1.1%. In our model we max pool over all $S''_{i,K_1}, \ldots, S''_{i,K_S}$ in our TABs. When we replace the max-pooling with concatenation + linear, we reach an accuracy of 37.4. We also try to disentangle the ensemble effect from the use of multi-granular representations. When we fix the spanning past scales $K$ to $\{15, 15, 15\}$ and all the starting points to $i = t - 20$, we observe a drop of 1.2% in accuracy which indicates the importance of our multi-scale representation.

| Method  | Input | Segmentation Method and Feature | Breakfast | 50 Salads |
|---------|-------|---------------------------------|-----------|----------|
| [40]    | FC7 features | [31], Fisher                  | 8.1       | 6.2      |
| RNN [1] | segmentation | [31], Fisher                  | 30.1      | 30.1     |
| CNN [1] | segmentation | [31], Fisher                  | 27.0      | 29.8     |
| ours no $Z$ | Fisher | -                              | 29.2      | 31.6     |
| ours $\{R(2+1)D\}$ | Fisher | -                              | 29.7      |          |
| ours     | I3D   | -                              | 32.3      |          |
| ours     | frame GT + I3D | ours, I3D                  | 40.1      |          |
| ours     | segmentation + I3D | ours, I3D                  | 43.1      |          |

Table 3. Next action anticipation on Breakfast and 50Salads and state-of-the-art comparisons, given different frame inputs as GT action labels, Fisher vectors and I3D features.

5.3 Anticipation on Procedural Activities - Breakfast Actions & 50 Salads

Next Action Anticipation predicts the action that occurs 1 second from the current time $t$. We compare to the state-of-the-art in Table 3 with two types of frame inputs: spatio-temporal features (Fisher vectors or I3D) and frame-wise action labels (either from ground truth or via a separate segmentation algorithm) on Breakfast actions. Compared to previous methods using only visual features as input, we outperform CNN (FC7) features [40] and spatio-temporal features R(2+1)D [28] by a large margin (+32.3% and +8.1%). While the inputs are different, R(2+1)D features were shown to be comparable to I3D features [39]. Given that [28] uses only recent observations, we conclude that incorporating the spanning past into the prediction model is essential.

As can be expected, our method degrades when we replace I3D with the weaker Fisher vectors (40.1% vs 29.7%). Nevertheless, this result is competitive with methods that use action labels [1] (30.1% with RNN) derived from segmentation algorithms [31] using Fisher vectors as input. For fair comparison, we report a variant without the complex activity prediction (“no $Z$”), which has a slight performance drop (-0.5%).

If we use action labels as inputs instead of visual features, our performance improves from 40.1% to 43.1%; merging labels and visual features gives another 4% boost.
### Table 4. Dense anticipation mean over frames accuracy on Breakfast and 50Salads, given different frame inputs as GT action labels, Fisher vectors and I3D features.

|                | 10%  | 20%  | 30%  | 50%  | 10%  | 20%  | 30%  | 50%  |
|----------------|------|------|------|------|------|------|------|------|
| **Breakfast**  |      |      |      |      |      |      |      |      |
| Pred           | 50.1 | 50.0 | 66.0 | 21.6 | 67.9 | 22.6 | 16.9 | 16.4 |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 13.5 | 22.4 | 20.1 | 44.2 | 10%  | 20%  | 30%  | 50%  |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 20.4 | 56.5 | 10.3 | 25.2 | 12.8 | 26.6 | 22.3 | 23.4 |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 25.6 | 9.8  | 18.7 | 10%  | 20%  | 30%  | 50%  |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 32.4 | 45.1 | 17.2 | 25.2 | 43.6 | 21.4 | 19.7 | 21.5 |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 31.7 | 25.6 | 22.4 | 16.4 | 34.2 | 27.4 | 22.6 | 15.9 |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 25.6 | 20%  | 23.1 | 16.0 | 27.1 | 22.1 | 15.6 |      |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 20%  | 45.3 | 18.6 | 24.7 | 19.8 | 27.9 | 50.1 | 32.3 |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 19.2 | 26.0 | 18.1 | 24.5 | 23.7 | 32.5 | 31.2 | 29.7 |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 33.9 | 32.1 | 34.6 | 27.6 | 23.0 | 17.8 | 36.1 | 27.9 |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 31.3 | 33.9 | 34.6 | 27.6 | 23.0 | 17.8 | 36.1 | 27.9 |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 17.9 | 16.4 | 15.4 | 14.5 | 22.4 | 20.1 | 19.7 | 18.8 |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 18.4 | 17.2 | 16.4 | 15.8 | 22.8 | 20.4 | 19.6 | 19.8 |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 27.6 | 25.0 | 24.5 | 23.7 | 32.5 | 31.2 | 29.7 |      |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 32.5 | 27.6 | 23.1 | 16.0 | 35.1 | 27.1 | 22.1 | 15.6 |
| Obs.           |      |      |      |      |      |      |      |      |
| Pred           | 31.7 | 25.6 | 22.4 | 16.4 | 34.2 | 27.4 | 22.6 | 15.9 |
| Obs.           |      |      |      |      |      |      |      |      |

In Table 4, we also report results for 50Salads. Using Fisher vectors we both outperform the state of the art by 1.8% and the baseline with CNN features [40] by 25.4%.

**Dense Anticipation** estimates frame-wise actions; accuracies are given for specific portions of the remaining video (Pred.) after observing a given percentage of the past (Obs.). We refer the reader to the supplementary for visual results. Competing methods [1] and [16] follow a two-stage setting where they use temporal video segmentation outputs [31], i.e. frame-wise action labels, as inputs. We experiment with both frame-wise labels and visual features. For Breakfast Actions (Table 4, left), when using GT frame labels, we outperform the others, with increasingly larger performance gaps for longer prediction horizons. In fact, we outperform competing methods [1] and [16] even when we use the same segmentation inputs (from [31], which has a frame-wise temporal segmentation accuracy of 36.8% and 42.9% for the observed 20% and 30% of video respectively). We observe further improvements once we substitute the segmentation algorithm with our own framework (I3D + ours). Similar to next action anticipation, performance drops when using only visual features as input (I3D is better than Fisher vectors). Interestingly, our method using even the weak Fisher vectors outperforms Ke et al. [16], which use frame-wise action labels from segmentation outputs.

We further merge visual features with action labels for dense anticipation. With Fisher vectors and the frame labels obtained from [31], we observe a slight increase in performance compared to only using the frame labels (up to +2%). When using I3D features and the frame label outputs of our segmentation method, we obtain our model’s best performance, with a slight increase over using only frame label outputs.
On 50Salads (see Table 4 right), when using ground truth frame label inputs, we are comparable to the state of the art [16]. Our predictions are more accurate on long-term anticipation (Pred. 50%). Using segmentation labels from [1] (frame-wise accuracy of 66.8% and 66.7% for 20% and 30% observed respectively), we are again comparable [16]. Finally, when we directly use the Fisher vectors as input to our model, we observe a slight decrease in performance. When using the Fisher vectors with the frame labels obtained from [31] we get better results than [16].

5.4 How much spanning past is necessary?

We vary the duration of spanning snippets (Eq. 3) with start time $i$ as fractions of the current time $t$; $i = 0$ corresponds to the full sequence, i.e., 100% of the spanning past, while $i = t$ corresponds to none, i.e., using only recent snippets since the end points $j$ remain fixed at $t$. Using the entire past is best for Breakfast (Fig. 4 left). Interestingly, this effect is not observed on EPIC (Fig. 4 right). Though we see a small gain by 1.2% until 40% past for the appearance features (rgb), beyond this, performance saturates.

![Fig. 4. Effect of spanning scope on instructional vs. daily activities. For EPIC (right) we report Top-5 accuracy on the validation set with rgb, optical-flow and object features and late fusion.](image)

We believe this has to do with the fine granularity of labels in EPIC; given that the median action duration is only 1.9s, one could observe as many as 16 actions in 30 seconds. Given that the dataset has only 28.5K samples split over 2513 action classes, we speculate that the model cannot learn all the variants of long-term relationships beyond 30 seconds. Therefore, increasing the scope of the spanning past does not further increase the performance, see Fig. 4 (right). Based on experiments on the validation set, we set the spanning scope to 6 seconds for EPIC for the rest of the paper. In Fig. 4, we report our results for appearance (rgb), optical flow and object-based features and the late fusion of the predictions from these modalities. Overall the appearance and object-based features outperform the optical-flow features.

5.5 Recognition and Anticipation on Daily Activities - EPIC-Kitchens

The anticipation task of EPIC-Kitchens requires anticipating the future action $\tau_\alpha = 1$s before it starts. For fair comparison to the state of the art [10] (denoted by “RU”), we use the same features (appearance, motion and object) provided by the authors. We train our model separately for each feature modality with the same parameters; during inference we apply a late fusion of the predictions from the different modalities by voting. Note that for experiments on this dataset we do not use the entire past for computing our spanning snippet features (see Section 5.4). We report our results for hold-out test data of EPIC-Kitchens used in the accompanying challenge\(^4\) in Table 5 for seen kitchens

\(^4\) https://competitions.codalab.org/competitions/20071
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Action Anticipation and Action Recognition on EPIC tests sets, seen (S1) and unseen (S2).

(S1) with the same environments as in the training data and unseen kitchens (S2) of held out environments. We outperform the Temporal Segment Networks of [5] for both Top-1 and Top-5 accuracy. We also outperform the state of the art RU [10] in the Top-1 and Top-5 action accuracies by 2% and 2.7% on S1 and by 1.8% and 2.3% on S2. The official ranking on the challenge is based on the Top-1 action accuracy. As of submission, our method is ranked first in the public leaderboard of the anticipation challenge (see supplementary).

For recognition, we follow the protocol of the EPIC-Kitchens Action Recognition Challenge\(^5\) to classify a pre-trimmed action segment. For this task we adjust the scope of our spanning and recent snippets according to the action start and end times \(t_a\) and \(t_e\). Spanning snippet features are computed on a range of \([t_a - 6, t_e + 6]\); the first recent snippet scope is fixed to \([t_a, t_e]\) and the rest to \([t_a - 1, t_e + 1], [t_a - 2, t_e + 2]\) and \([t_a - 3, t_e + 3]\). Remaining parameters are kept the same. In Table 5, we compare our results to the state-of-the-art methods. We show that our model outperforms the other recognition methods including the state of the art SlowFast networks with audio data [45] (+5.4% on S1, +2.2% on S2 for Top-1 Accuracy). We also outperform Long-term Feature Banks [44], which also uses non-local blocks (+8.6% on S1, +5% on S2 for Top-1). We also show that our method outperforms [10] by approximately +7% on both S1 and S2. Together with the anticipation results from the previous paragraph, we can conclude that our method generalizes to both anticipation and recognition tasks and is able to achieve state-of-the-art results on both, while [10] performs very well on anticipation but poorly on recognition.

Besides predicting the next actions for \(\tau_\alpha = 1s\), [10] also report prediction results at multiple anticipation times between 0.25s and 2s on EPIC. We compare in Table 6 the validation set and note that our prediction scores are better than [10] for all time points, where our improvements are greater when the anticipation time decreases.

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\(^5\) https://competitions.codalab.org/competitions/20115
Table 7. Exemplary segmentation and comparison with the state of the art on Breakfast Actions.

| Model                      | Frame-wise Acc | Segmental Edit Dist | F1@{10, 25, 50} | Edit Acc |
|----------------------------|----------------|---------------------|------------------|----------|
| MS-TCN (I3D) [8]           | 52.6           | 48.1                | 37.9             | 61.7     |
| ours I3D 2s                | 52.3           | 46.5                | 34.8             | 51.3     |
| ours I3D 5s                | 59.2           | 53.9                | 39.5             | 54.5     |
| ours I3D GT.seg.           | -              | -                   | -                | 75.9     |

5.6 Temporal Video Segmentation

We compare our performance against the state of the art, MS-TCN (I3D) [8], in Table 7 on Breakfast. We test our model with 2s and 5s windows. We report the frame-wise accuracy (Acc), segmental edit distance and F1 scores at overlapping thresholds of 10%, 25% and 50%. In the example sequences, in the F1 scores and edit distances in Table 7, we observe more fragmentation in our segmentation for 2s than for 5s. However, for 2s, our model produces better accuracies, as the 5s windows are smoothing the predictions at action boundaries. Additionally we provide our model’s upper bound, “ours I3D GT.seg.”, for which we classify GT action segments instead of sliding windows. The results indicate that there is room for improvement, which we leave as future work. We show that we are able to easily adjust our method from its main application and already get close to the state of the art with slight modifications.

6 Discussion & Conclusion

In this paper, we presented a temporal aggregate model for long-term video. Our method computes recent and spanning representations pooled from snippets of video that are related via coupled attention mechanisms for encoding multi-granular long-term action video. Validating on three complex activity datasets, we show that temporal aggregates are either comparable or outperform the state of the art on three video understanding tasks: action anticipation, recognition and temporal video segmentation.

In developing our framework, we faced questions regarding temporal extent, scaling, and level of semantic abstraction. From our experiments, we found that max-pooling is a simple and efficient yet effective way of representing video snippets; this is the case even for snippets as long as two minutes. For learning temporal relationships in long video, we observe that attention mechanisms that relate the present information to long term context can successfully model and anticipate upcoming actions. The extent of long-term context that is beneficial, however, seems to depend on the nature of activity (instructional vs. daily) and label granularity (coarse vs. fine) of the dataset.

We found significant advantages to using ensembles of multiple scales, both in the recent and spanning snippets. The flexibility of our temporal aggregates model allows us to incorporate the entire ensemble and to achieve state-of-the-art performance for both visual features and action label inputs. Our experiments confirm that higher levels of abstraction such as frame-wise action labels are more preferable for anticipation, thought there is still a large gap between what can be anticipated with inputs from current segmentation algorithms in comparison to ground truth labels. Our proposed framework is composed of simple, yet effective building blocks for encoding long-term information and thus has potential for video understanding in general.
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Supplementary - Temporal Aggregate Representations for Long Term Video Understanding

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1 More on Datasets and Features

We provide more statistics about the datasets used in our paper to show a broader comparison about their scale and label granularity.

The Breakfast Actions dataset [7] contains 1712 videos of 10 high level tasks like “making coffee”, “making tea” and so on. There are in total 48 different actions, such as “pouring water” or “stirring coffee”, with on average 6 actions per video. The average duration of the videos is 2.3 minutes. There are 4 splits and we report our results averaged over them. We use two types of frame-wise features: Fisher vectors computed as in [1] and I3D features [2].

The 50Salads dataset [9] includes 50 videos and 17 different actions for a single task, namely making mixed salads. When training on this dataset, we therefore omit task prediction in our model. On average, 50Salads has 20 actions per video due to repetitions. The average video duration is 6.4 minutes. There are 5 splits, and we again average our results over them. We represent the frames using Fisher vectors as in [1].

The EPIC-Kitchens dataset [3] is a large first-person video dataset which contains 432 sequences and 39,594 action segments recorded by participants performing non-scripted daily activities in their kitchen. The average duration of the videos is 7.6 minutes ranging from 1 minute to 55 minutes. An action is defined as a combination of a verb and a noun, e.g. “boil milk”. There are in total 125 verbs, 331 nouns and 2513 actions. The dataset provides a training, validation and test set which contain 232, 40 and 160 videos respectively. The test set is divided into two splits: Seen Kitchens (S1) where sequences from the same environment are in the training data, and Unseen Kitchens (S2) where complete sequences of some participants are held out for testing. The labels for the test set are not shared, as there is an action anticipation challenge³. We use the RGB, optical flow and object-based features provided by Furnari and Farinella et al. [5].

2 Model Validation

For validating our method’s capabilities in modelling sequences, we make baseline comparisons. The simplest approach for solving the next action anticipation task is

³ https://competitions.codalab.org/competitions/20071
using a transition matrix (TM) [8], which encodes the transition from one action to the next. A more sophisticated solution is building a lookup table (LUT) of varying length sequences which allows encoding the context in a more explicit manner. The problem with LUTs is that their completeness depends on the coverage of the training data, and they rapidly grow with the number of actions. So far, for next step prediction, RNNs achieve good performance [1], as they learn modelling the sequences.

For our baseline comparisons, instead of frame features, we use the frame-level ground truth labels as input to our model. We compute the TM, LUT and RNN on the ground truth segment-level labels. In Table 1 we present comparisons on the Breakfast Actions for the next action anticipation per complex activity. Overall, transition matrices provide the worst results. LUTs improve the results, as they incorporate more contextual information. Both the RNN and our method outperform the other alternatives, while our method still performs better than the RNN on average. However, applying RNNs requires parsing the past into action sequences [1], which turns the problem into separate segmentation and prediction phases. Our model, on the other hand, can be trained end-to-end, and can represent the long-term observations good enough to outperform RNNs. We show that our model is doing better than simply learning pairwise statistics of the dataset.

### Table 1. Model validation using GT labels for next action anticipation on Breakfast Actions, presented are accuracies. We compare transition matrices (TM), lookup tables (LUT), RNNs and our temporal aggregates model (without complex activity prediction).

|       | cereal | coffee | f.egg | juice | milk | panc. | salat | sand. | s.egg | tea | mean ± std |
|-------|--------|--------|-------|-------|------|-------|-------|-------|-------|----|------------|
| TM    | 49.3   | 30.6   | 44.0  | 60.7  | 27.0 | 33.2  | 40.9  | 55.5  | 53.0  | 26.2| 45.0 ±12.7 |
| LUT   | 57.5   | 58.5   | 53.0  | 63.7  | 56.1 | 52.5  | 47.0  | 49.1  | 59.0  | 60.8| 54.7 ±5.2  |
| RNN   | 79.8   | 47.2   | 52.9  | 61.2  | 72.7 | 73.9  | 64.3  | 46.9  | 60.5  | 68.7| 63.1 ±11.3 |
| ours  | 69.8   | 54.7   | 62.5  | 65.7  | 72.9 | 66.2  | 63.6  | 64.6  | 58.0  | 64.1| 64.2 ±5.2  |

#### 3 Visual Results

In Fig. 1, we provide qualitative results from our method for dense anticipation on the Breakfast Actions dataset. We show our method’s predictions after observing 30% of the video. We compare our results when we use the GT labels and I3D features as input.

In Fig. 2, we present qualitative results from our method for next action anticipation on the EPIC-Kitchens dataset for multiple anticipation times \( \tau \) between 0.25 and 2 seconds. We show examples where our method is certain about the next action for all different times. We also show examples where our method’s prediction gets more accurate when the anticipation time is closer.

In Fig. 3, we present some visualizations of regions attended by our non-local blocks. We show the five highest weighted spanning snippets (at different granularities). Our model attends different regions over the videos, for example for predicting ‘fry egg’ when making fried eggs, it attends regions both when pouring oil and cracking eggs. Pouring oil is an important long-term past action for frying eggs. Our method can encode long video durations while attending to salient snippets.
Fig. 1. Qualitative results for dense anticipation on Breakfast Actions dataset when using the GT labels and I3D features. Best viewed in color.

4 Action Anticipation Challenge on EPIC-Kitchens

We present a screenshot of the EPIC-Kitchens action anticipation challenge which was taken on the 3rd of March, 2020, in Fig. 4. The official ranking on the challenge is based on the Top-1 action accuracy. Our submission (name “action_banks”) is ranked first on both the S1 and S2 sets. Note that there might be changes in the leader-board as the challenge website is open until the 29th of May and allows revealing submissions at any time on the leader-board.

Based on the results reported in the EPIC-Kitchens 2019 Challenges Report [4], two of the participants have published works. The team name “antoninofurnari” is the work presented by Furnari and Farinella [5] (RU). We use the same features as in this method and outperform their results. “EPIC_TSN_RGB” is presented by Damen et al. [3] where they use temporal segment networks over RGB features for predicting the noun and verb for next action.
Fig. 2. Exemplary qualitative results for next action anticipation on EPIC-Kitchens dataset, showing the success of our method. We list our Top-5 predictions at different anticipation times, \( \tau_\alpha \). The closer we are the better are our model’s predictions. Best viewed in color.

5 Action Recognition Challenge on EPIC-Kitchens

In Fig. 5 we present a screenshot of the EPIC-Kitchens action recognition challenge, again taken on the 3rd of March, 2020. Like the action anticipation challenge, this one is also officially ranked by the Top-1 action accuracy. Here, our submission (team name “action_banks”) is ranked first on the S1 and third on the S2 test sets. Note again that there might be changes in the leader-board as the challenge website is open until the 29th of May and allows revealing submissions at any time on the leader-board.
Fig. 3. Attention visualization on the Breakfast Actions dataset for next action anticipation. Rectangles are the top 5 five spanning snippets (at different granularities where $K = 10,15,20$), weighted highest by the attention mechanism in the Non-Local Blocks (NLB). Best viewed in color.

In the EPIC-Kitchens 2019 Challenges Report [4] two of the participants report published works. The team name “antoninofurnari” corresponds to the work presented by Furnari and Farinella [5] (RU). As in the action anticipation setting, we use the same features as in this method and again outperform their results. “TBN_Ensemble” is proposed by Kazakos et al. [6] who utilize RGB, flow, and audio, along with an approach for temporal binding of modalities based on temporal segment networks. Our method outperforms theirs. Motivated by the success of the audio features in this work [6], we plan to incorporate audio into our network as future work. When comparing to the methods that rank better than ours (“aptx4869lm” and “weiyaowang”) on S2, ours shows around 1.2% less performance in the Top-1 action accuracy. However, we cannot make any further direct comparisons with these methods as we do not know the features and models used by them.
Fig. 4. Screenshots of the EPIC-Kitchens Action Anticipation Challenge Leaderboards acquired from https://competitions.codalab.org/competitions/20071 on the 3rd of March, 2020. Note that our best model was submitted under the name “action_banks”.
Fig. 5. Screenshots of the EPIC-Kitchens Action Recognition Challenge Leaderboards acquired from https://competitions.codalab.org/competitions/20115 on the 3rd of March, 2020. Note that our best model was submitted under the name “action_banks”.
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