Knowledge Distillation for Action Anticipation via Label Smoothing

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Abstract—Human capability to anticipate near future from visual observations and non-verbal cues is essential for developing intelligent systems that need to interact with people. Several research areas, such as human-robot interaction (HRI), assisted living or autonomous driving need to foresee future events to avoid crashes or help visually impaired people. Such challenging task requires to capture and understand the underlying structure of the analyzed domain in order to reduce prediction uncertainty. Since the action anticipation task can be seen as a multi-label problem with missing labels, we design and extend the idea of label smoothing extracting semantics from the target labels. We show that such generalization is equivalent to considering a knowledge distillation framework where a teacher injects useful semantic information into the model during training. In our experiments, we implement a multi-modal framework based on long short-term memory (LSTM) networks to anticipate future actions which is able to summarise past observations while making predictions of the future at different time steps. To validate our soft labeling procedure we perform extensive experiments on the egocentric EPIC-Kitchens dataset which includes more than 2500 action classes. The experiments show that label smoothing systematically improves performance of state-of-the-art models.

I. INTRODUCTION

Human action analysis is a central task in computer vision that has an enormous impact on many applications, such as, video content analysis [1], [2], video surveillance [3], [4], and automated driving vehicles [5], [6]. Systems interacting with humans also need the capability to promptly react to the context changes, and plan their actions accordingly. Most previous works focus on the tasks of action recognition [7], [8], [9] or early-action recognition [10], [11], [12], i.e., recognition of an action after its observation (happened in the past) or recognition of an ongoing action from its partial observation (only part of the current action is available). A more challenging task is to predict near future, i.e., to forecast actions that will be performed ahead in time. Predicting future actions before observing the corresponding frames [13], [14] is demanded by many applications which need to anticipate human behaviour. For example, intelligent surveillance systems may support human operators to avoid hazards or assistive robotics may help non-self-sufficient people. Such task requires to analyze significant spatio-temporal variations among actions performed by different people. For this reason, multiple modalities (e.g., appearance and motion) are typically considered to improve the identification of similar actions. Egocentric scenarios provide useful settings to study early-action recognition or action anticipation tasks. Indeed, wearable cameras offer an explicit point-of-view to capture human motion and object interaction.

In this work, we address the problem of anticipating egocentric human actions in an indoor scenario at several time steps. More specifically, we anticipate an action by leveraging video segments that precede the action. We disentangle the processing of the video into encoding and decoding stages. In the first stage, the model summarizes the video content while in the second stage the model predicts at multiple anticipation times \( \tau_a \) the next action (see Fig. 1). We exploit a recurrent neural network (RNN) to capture temporal correlations between subsequent frames and consider three different modalities for representing the input: appearance (RGB), motion (optical flow) and object-based features. An important aspect to consider when dealing with human action anticipation is that the future is uncertain, which means that different prediction of future actions are equally likely to occur. For example, the actions “sprinkle over pumpkin seeds” and “sprinkle over sunflower seeds” may be equally performed when preparing a recipe. For this reason, to deal with the uncertainty of future
predictions, we propose to group similar actions comparing several label smoothing techniques in order to broaden the set of possible futures and reduce the uncertainty caused by one-hot encoded labels. Label smoothing is introduced in [15] as a form of regularization for classification models since it introduces a positive constant value into wrong classes components of the one-hot target. A peculiar feature of such method is to make models robust to overfitting especially when labels in the dataset are noisy, e.g., the targets are ambiguous. In our work, we extend label smoothing by using them as a bridge for distilling knowledge into the model during training. Our experiments on the large-scale EPIC-Kitchens dataset show that label smoothing increases the performance of state-of-the-art models and yields better generalization on test data.

The main contributions of our work are as follows: 1) we generalize the label smoothing idea extrapolating semantic priors from the action labels to capture the multi-modal future component of the action anticipation problem. We show that label smoothing, in this context, can be seen as a knowledge distillation process where the teacher gives semantic prior information for the action anticipation model; 2) we perform extensive experiments on egocentric videos proving that our label smoothing techniques systematically improve results of action anticipation of state-of-the-art models.

II. RELATED WORK

Action anticipation requires the interpretation of the current activity using a number of observations in order to foresee the most likely actions. For this reason, we briefly review three related research areas: action recognition, early-action recognition and action anticipation.

Action recognition. Action recognition is the task of recognizing the action contained in an observed trimmed video. Classic approaches to action recognition have leveraged hand-designed features, coupled with machine learning algorithms to recognize actions from video [7], [16], [17]. More recent works have investigated the use of deep learning to obtain representations suitable for action recognition directly from video in an end-to-end fashion. Among these approaches, a line of works has investigated ways to exploit standard 2D CNNs for action recognition, often relying on optical flow as a mean to represent motion [8], [13], [9], [19], [20], [21]. Other works have focused on the extension of 2D CNNs to 3D CNNs able to process spatio-temporal volumes [2], [22], [23]. Some approaches have used recurrent networks to model the temporal relationships between per-frame observations [24], [25], [14]. All of these works investigate deepley how to represent and leverage the input video but less or even no importance is given to the representation of the action labels.

Early-action recognition. Early action recognition consists in recognizing on-going actions from partial observations of streaming video [12]. Classic works have addressed the task using integral histograms of spatio-temporal features [10], sparse-coding [11], Structured Output SVMs [26], and Sequential Max-Margin event detectors [27]. Another line of research has leveraged the use LSTMs [28], [29], [30], [14] to account for the sequential nature of the task.

Action anticipation. Action anticipation deals with forecasting actions that will happen in the future. Previous studies have investigated different approaches such as hierarchical representations [31], auto-regressive HMMs [32], regressing future representations [33], using encoder-decoder LSTMs [34], and inverse reinforcement learning [35]. Some other approaches proposed to perform long-term predictions focusing only on appearance features [36], [37]. However, differently from this work, very little or even no attention has been payed either to the knowledge distillation of the action semantics or label smoothing for action anticipation.

Knowledge distillation and label smoothing. Knowledge distillation [38] is the procedure of transferring the information extracted by a teacher network (with high learning capacity) to a student network (with low learning capacity) in order to allow the latter to reach similar performance. This is usually obtained by training the student via a distillation loss which takes into account both the ground truth and the prediction of the pre-trained teacher. Since this procedure can distill useful information form the teacher to the student, we perform semantic distillation via label smoothing.

Label smoothing, introduced in [15], is the procedure of softening the distribution of the target labels, reducing the most confident value of the one-hot vector and considering a uniform value for all the zero vector components. Although such procedure improves results for classification problems reducing overfitting, no previous works investigate other design approaches except for the uniform smoothing. In our work, we both generalize this idea and show a systematically improvement of state-of-the-art models.

III. PROPOSED APPROACH

Anticipating human actions is essential for developing intelligent systems able to avoid accidents or guide people to correctly perform their actions. We study the suitability of label smoothing techniques to address the issue.

A. Label Smoothing

As investigated in [39], there is an inherent uncertainty on predicting future actions. In fact, starting from the current state observation of an action there can be multiple, but still plausible, future scenarios that can occur. Hence, the problem can be reformulated as a multi-label task with missing labels where, from all the valid future realizations, only one is sampled from the dataset. All previous models designed for action anticipation are trained with cross-entropy using one-hot labels, leveraging only one of the possible future scenario as the ground truth. A major drawback of using hard labels is to favour logits of correct classes weakening the importance of other plausible ones. In fact, given the one-hot encoded vector \( y^{(k)} \) for a class \( k \), the prediction of the model \( p \) and the logits of the model \( z \) such that \( p(i) = e^{z(i)} / \sum_{j} e^{z(j)} \), the cross entropy is minimized only if \( z(k) \gg z(i) \forall i \neq k \). This fact
Fig. 2: Action anticipation protocol based on the encoding and decoding stages. We summarize past observations by processing video snippets sampled every $\alpha = 0.25$ seconds in the encoding stage. After 6 steps, we start making predictions every $\alpha$ seconds for 8 steps to anticipate the future action.

Fig. 3: Encoding (left) and decoding (right) of our architecture. The encoding block takes as input the video snippet represented by three modalities (optical flow, RGB and objects). Each modality is separately fed into an LSTM. The decoding block is composed by three LSTM branches that take as input the processed video snippets. We apply dropout at each branch. Finally, all the branches are concatenated and passed to a fully connected layer with softmax activation.

encourages the model to be over-confident about its predictions since during training it tries to focus all the energy on one single logit leading to overfitting and scarce adaptivity [15]. To this purpose, we smooth the target distribution enabling the chance of negative classes to be plausible. However, the usual label smoothing procedure introduces a uniform positive component among all the classes, without capturing the difference between actions. To this end, we propose several ways of designing such smoothing procedure by encoding semantic priors into the labels and weighting the actions according their feature representation. We can connect our soft labels approach to the knowledge distillation framework [38] where the teacher randomly predicts the output, i.e., $p_{\text{teacher}}(i) = 1/K, \forall i$. Hence, the connection with the distillation loss proves that the second term in Eq. (1) can be seen as a prior knowledge, given by an agnostic teacher, for the target $y$. Although using an agnostic teacher seems an unusual choice, uniform label smoothing can be seen as a form of regularization [15] and thus it can improve the model’s generalization capability. Taking this into account, we extend the idea of smoothing labels by modeling the second term of Eq. (1), i.e., the prior knowledge of the targets, as follows:

$$y^{\text{soft}}(i) = (1 - \alpha)y(i) + \alpha/K,$$

(1)

where $y$ is the one-hot encoding, $\alpha$ is the smoothing factor ($0 \leq \alpha \leq 1$) and $K$ represents the number of classes. Since cross entropy is linear w.r.t. its first argument, it can be written as follows:

$$CE[y^{\text{soft}}, p] = \sum_i -y^{\text{soft}}(i) \log(p(i)) = (1 - \alpha)CE[y, p] + \alpha CE[1/K, p].$$

(2)

The optimization based on the above loss can be seen as a distillation knowledge procedure [38] where the teacher randomly predicts the output, i.e., $p_{\text{teacher}}(i) = 1/K, \forall i$. Hence, the connection with the distillation loss proves that the second term in Eq. (1) can be seen as a prior knowledge, given by an agnostic teacher, for the target $y$. Although using an agnostic teacher seems an unusual choice, uniform label smoothing can be seen as a form of regularization [15] and thus it can improve the model’s generalization capability. Taking this into account, we extend the idea of smoothing labels by modeling the second term of Eq. (1), i.e., the prior knowledge of the targets, as follows:

$$y^{\text{soft}}(i) = (1 - \alpha)y(i) + \alpha \pi(i),$$

(3)

where $\pi \in \mathbb{R}^K$ is the prior vector such that $\sum_i \pi(i) = 1$ and $\pi(i) \geq 0 \forall i$.

Therefore, the resulting cross entropy with soft labels is written as follows:

$$CE[y^{\text{soft}}, p] = (1 - \alpha)CE[y, p] + \alpha CE[\pi, p]$$

(4)

This loss not only penalizes errors related to the correct class but also errors related to the positive entries of the prior. Starting from this formulation, we introduce Verb-Noun, GloVe
and Temporal priors for smoothing labels in the knowledge distillation procedure. In the following, we detail our label smoothing techniques.

**Verb-Noun label smoothing.** EPIC-KITCHENS [13] contains action labels structured as verbs-noun pairs, like “cut onion” or “dry spoon”. More formally, if we define $A$ the set of actions, $V$ the set of verbs, and $N$ the set of nouns, then an action is represented by a tuple $a = (v, n)$ where $v \in V$ and $n \in N$. Let $A_v(\bar{v})$ the set of actions sharing the same verb $\bar{v}$ and $A_n(\bar{n})$ the set of actions sharing the same noun $\bar{n}$, defined as follows:

$$A_v(\bar{v}) = \{(\bar{v}, n) \in A \; n \in N\},$$

$$A_n(\bar{n}) = \{(v, \bar{n}) \in A \; v \in V\},$$

where $\bar{n} \in N$ and $\bar{v} \in V$.

We define the prior of the $k^{th}$ ground-truth action class as

$$\pi_{GN}^{(k)}(i) = \frac{1}{C_k} \left[ a(i) \in A_v(v(k)) \cup A_n(n(k)) \right],$$

where $a(i)$ is the $i^{th}$ action, $v(k)$ and $n(k)$ are the verb and the noun of the $k^{th}$ action, $\mathbb{1}[:i]$ is the indicator function, and $C_k = |A_v(v(k))| + |A_n(n(k))| - 1$ is a normalization term. Using such encoding rule, the cross entropy not only penalizes the error related to the correct class but also the errors with respect to all the other “similar” actions with either the same verb or noun.

**GloVe based label smoothing.** An important aspect to consider when dealing with actions represented by verbs and/or nouns is their semantic meaning. In the Verb-Noun label smoothing, we define the prior considering a rough yet still meaningful semantic where actions that share either the same verb or noun are considered similar. To extend this idea, we extrapolate the prior from the word embedding of the action. One of the most important properties of word embeddings is to put closer words with similar semantic meanings and to move dissimilar ones far away, as opposed to hard labels that cannot capture at all similarity between classes since $y(i)^T y(j) = 0 \; \forall i \neq j$.

Using such representation, we enable the distillation of useful information into the model during training since the cross entropy not only penalizes the error related to the correct class but also the error related to all other similar actions. In order to compute the word embeddings of the actions we use the GloVe model [40] pretrained on the Wikipedia 2014 and Gigaword 5 datasets. We use the GloVe model since it does not rely just on local statistics of words, but incorporates global statistics to obtain word vectors. Since the model takes as input only single words, we encode the action as follows:

$$\phi^{(k)} = Concat \left[GloVe(v^{(k)}), GloVe(n^{(k)})\right]$$

1\ text can be proved that in terms of scalar product two different classes having the same noun or verb and encoded with Verb-Noun label smoothing are closer respect to classes encoded with hard labels.

| Temporal Uniform Verbl-Noun GloVe GloVe+Verb-Noun | $\alpha$ | 0.6 | 0.1 | 0.45 | 0.6 | 0.5 |
|-----------------------------------------------|---------|-----|-----|------|-----|-----|

**TABLE I: Results of a grid search procedure to detect the best smooth factor $\alpha$ for proposed label smoothing techniques.**

where $\phi$ is the obtained action representation of $a^{(k)} = (v(k), n(k))$ and $\text{GloVe}(\cdot) \in \mathbb{R}^{300}$ is the output of the GloVe model. We finally compute the prior probability for smoothing the labels as the similarity between two action representations, which is computed as follows:

$$\pi_{GL}^{(k)}(i) = \frac{|\phi(k)^T \phi(i)|}{\sum_j |\phi(k)^T \phi(j)|}.$$  

Hence, $\pi_{GL}^{(k)}(i)$ in Eq. 9 represents the similarity between the $k^{th}$ and the $i^{th}$ action.

**Temporal label smoothing.** Some actions are more likely to co-occur than others. Furthermore, only specific action sequences may be considered plausible. For this reason, it could be reasonable to focus on most frequent action sequences since they may reveal possible valid paths in the actions space. In this case, we build the prior probability of their observation by considering subsequent actions of length two, i.e., we estimate from the training set the transition probability from the $i^{th}$ to the $k^{th}$ action as follows:

$$\pi_{TE}^{(k)}(i) = \frac{\text{Occ} \left[ a(i) \rightarrow a^{(k)} \right]}{\sum_j \text{Occ} \left[ a(j) \rightarrow a^{(k)} \right]}$$

where $\text{Occ} \left[ a(i) \rightarrow a^{(k)} \right]$ is the number of times that the $i^{th}$ action is followed by the $k^{th}$ action. Using such representation, we reward both the correct class and most frequent actions that precede the correct class.

**B. Action Anticipation Architecture**

For our experiments, we consider a learning architecture based on recurrent neural networks. Following [14], our approach uses the protocol depicted in Fig. 2 for anticipating future actions. We process the frames preceding the action that we want to anticipate grouping them into video snippets of length 5. Each video snippet is collected every $\alpha = 0.25$ seconds and processed considering three different modalities: RGB features computed using a Batch Normalized Inception CNN [11] trained for action recognition, objects features computed using Fast-R CNN [32] and optical flow computed as in [19], processed through a Batch Normalized Inception CNN trained for action recognition. Our multi-modal architecture processes the above inputs and encompasses two building blocks: an encoder which recognizes and summarises past observations and a decoder which predicts future actions at different anticipation time steps. As shown in Fig. 3 during the encoding stage each modality is separately processed by a LSTM layer. During the decoding stage such streams are then merged with late fusion and fed into a fully connected layer using softmax activation.
IV. EXPERIMENTS

A. Dataset and Evaluation Measures

Dataset. Our experiments are performed on the EPIC-KITCHENS [13] dataset. This is a large-scale collection of egocentric videos that contains 39,596 action annotations divided into 2513 unique actions, 125 verbs, and 352 nouns. We use the same split as [14] producing 23,493 segments for training and 4,979 segments for validation.

Evaluation Measures. To assess the quality of predictions and compare all methods, we use the Top-k accuracy, i.e., we assume the prediction correct if the label falls into the best top-k predictions. As reported in [59], [43], such measure is one of the most appropriate given the uncertainty of future predictions. More specifically, we use the Top-5 accuracy for methods comparison. For the test set, we also use the Top-1 accuracy, the Macro Average Class Precision and the Macro Average Class Recall. The last two metrics are computed only on many-shot nouns, verbs and actions as explained in [13].

B. Models and Baselines

In the comparative analysis, we exploit the architecture proposed in Sec. III-B employing the different label smoothing techniques defined in Sec. III-A. In our experiments we consider models trained using one-hot vectors (One Hot), uniform smoothing (Smooth Uniform), temporal soft labels (Smooth TE), Verb-Noun soft labels (Smooth VN), GloVe based soft labels (Smooth GL) and GloVe + Verb-Noun soft labels (Smooth GL+VN). We design the last method (Smooth GL+VN) by smoothing hard labels with the average of the two related priors. We also evaluate the effect of the proposed label smoothing techniques on the state-of-the-art approach RU-LSTM [14]. In this case, we choose GL+VN as label smoothing technique.

To implement the architecture, we used TensorFlow 2. Each model is trained for 100 epochs with batch size of 256 using Adam optimizer with learning rate of 0.001. The best model is selected using early stopping by monitoring the Top-5 accuracy at anticipation time $\tau_0 = 1$ on the validation set.

Results. For each label smoothing method we select the best smooth factor $\alpha^*$ with a grid search procedure between 0 and 1 and step size $\Delta \alpha = 0.05$. The smooth factors used for the results discussed in this section are shown in Table I.

We notice that our label smoothing procedures such as Verb-Noun, GloVe and Temporal perform well with higher smooth factors ($\alpha^* \simeq 0.5$) compared to Uniform label smoothing ($\alpha^* = 0.1$). This suggests that, when soft labels encodes semantic information, prior information becomes more relevant assuming the same importance of the ground-truth due to the similar smooth factors ($\alpha \simeq 1 - \alpha$). During training, we fix $\alpha = \alpha^*$ for each method and, in order to have a robust performance estimation among trials, we iterate ten times all the experiments.

Table I reports our results on the EPIC-KITCHENS validation set. We notice that all our proposed label smoothing methods improve model performance as compared with training using one-hot encoded labels. Soft labels based on GloVe + Verb-Noun attain best performance improving the Top-5 accuracy from +1.17% to +2.13% compared to hard labels. To validate our results, we trained [14], the state-of-the-art model for action anticipation, considering label smoothing using EPIC-KITCHENS validation and test sets. Table II reports results of RU-LSTM architecture using both one-hot encoding (i.e., the baseline) and smoothed labels on the validation set. We select GloVe + Verb-Noun soft labels since they show a higher performance increase. As shown by the obtained results, label smoothing improves the Top-5 accuracy for all the anticipation times of a margin from +%0.58 to +%1.59%. Such behavior highlights the systematic effect of smoothed labels on the model performance.

In Table IV we report the results obtained considering the test set of EPIC-KITCHENS. Different approaches are considered for the comparison. It is worth noting that the method which consider label smoothing together with RU-LSTM improves the performances obtaining best Top-1 and Top-5 accuracy for anticipating verb, noun and action. Label smoothing helps also to improve Precision for verb and obtains comparable results in anticipating action and noun. Results in terms of Recall point out that label smoothing helps for noun anticipation maintaining comparable results for the anticipation of verb and action. Finally, Fig. 4 shows some qualitative results obtained with our framework, whereas Fig. 5 depicts prior component representations of the proposed label smoothing procedures.

V. CONCLUSION

This study proposed a knowledge distillation procedure via label smoothing for leveraging the multi-modal future component of the action anticipation problem. We generalized the idea of label smoothing by designing semantic priors of actions that are used during training as ground truth labels. We implemented a LSTM baseline model that can anticipate actions at multiple time steps starting from multi-modal representation of the input video. Experimental results corroborate out findings compared to state-of-the-art models highlighting that label smoothing systematically improves performance when dealing with future uncertainty.

Acknowledgements: Research at the University of Padova is partially supported by MIUR PRIN-2017 PREVUE grant. Authors of Univ. of Padova gratefully acknowledge the support of NVIDIA for their donation of GPUs, and the UNIPD CAPRI Consortium, for its support and access to computing resources. Research at the University of Catania is supported by Piano della Ricerca 2016-2018 linea di Intervento 2 of DMI and MIUR AIM - Attrazione e Mobilit Internazionale Linea 1 - AIM1893589 - CUP E64118002540007.
TABLE II: Top-5 accuracy for action anticipation task at different anticipation time steps on EPIC-KITCHENS validation set. We report results of several label smoothing techniques and show a systematic performance improvement compared to one-hot encoded labels.

| Top-5 Action Accuracy % @ different anticipation times [s] |
|---------------------------------------------------------|
| 2  | 1.75 | 1.5 | 1.25 | 1 | 0.75 | 0.5 | 0.25 |
| One Hot (baseline) | 27.71 ±0.33 | 28.69 ±0.34 | 29.84 ±0.24 | 30.90 ±0.48 | 31.93 ±0.45 | 33.14 ±0.36 | 34.10 ±0.44 | 35.16 ±0.35 |
| Smooth TE | 27.94 ±0.24 | 28.90 ±0.27 | 30.06 ±0.24 | 31.13 ±0.19 | 32.19 ±0.28 | 33.21 ±0.36 | 34.17 ±0.37 | 35.10 ±0.25 |
| Smooth Uniform | 28.16 ±0.27 | 29.06 ±0.26 | 30.23 ±0.28 | 31.25 ±0.27 | 32.41 ±0.28 | 33.66 ±0.27 | 34.69 ±0.19 | 35.75 ±0.13 |
| Smooth VN | 28.43 ±0.30 | 29.41 ±0.31 | 30.68 ±0.28 | 31.85 ±0.21 | 33.08 ±0.18 | 34.35 ±0.19 | 35.38 ±0.34 | 36.46 ±0.26 |
| Smooth GL | 28.61 ±0.26 | 29.87 ±0.25 | 30.97 ±0.34 | 31.94 ±0.34 | 33.12 ±0.36 | 34.40 ±0.37 | 35.51 ±0.37 | 36.87 ±0.25 |
| Smooth GL+VN | 28.88 ±0.20 | 29.94 ±0.19 | 31.23 ±0.32 | 32.54 ±0.31 | 33.56 ±0.28 | 34.92 ±0.25 | 36.06 ±0.33 | 37.29 ±0.03 |
| Improv. | +1.17 | +1.25 | +1.39 | +1.64 | +1.63 | +1.78 | +1.96 | +2.13 |

TABLE III: Top-5 accuracy for action anticipation task at different anticipation time steps on EPIC-KITCHENS validation set. We introduce GL+VN smoothing technique into state-of-the-art RU-LSTM [14] model.

| Top-5 Action Accuracy % @ different anticipation times [s] |
|---------------------------------------------------------|
| 2  | 1.75 | 1.5 | 1.25 | 1 | 0.75 | 0.5 | 0.25 |
| RU-LSTM | 29.44 ±0.37 | 30.73 ±0.44 | 32.24 ±0.44 | 33.81 ±0.35 | 35.32 ±0.34 | 37.37 ±0.38 | 38.99 ±0.74 |
| RU-LSTM Smooth GL + VN | 30.37 ±0.31 | 31.64 ±0.34 | 33.17 ±0.34 | 34.86 ±0.35 | 35.90 ±0.37 | 37.07 ±0.38 | 39.06 ±0.74 |
| Improv. | +0.93 | +0.91 | +0.93 | +1.45 | +0.58 | +0.73 | +1.59 | +1.36 |

TABLE IV: Results of action anticipation on the test sets of EPIC-Kitchens. The test set is divided into kitchens already seen S1 or unseen S2 from the model. The table confirms also on the test set that our smoothing labels procedure can improve performances of the state-of-the-art model RU-LSTM.

| VERB | NOUN | ACTION |
|------|------|--------|
| DMRI [33] | 26.53 | 10.43 | 01.27 |
| 2SCNN [13] | 27.96 | 15.15 | 04.32 |
| RTSN [12] | 31.81 | 16.22 | 06.00 |
| MCE [59] | 27.92 | 16.09 | 10.76 |
| ED [24] | 29.25 | 16.07 | 08.08 |
| Miech et al. [44] | 30.74 | 16.47 | 09.74 |
| RU-LSTM [14] | 33.04 | 22.78 | 14.39 |
| RU-LSTM Smooth GL + VN | 35.04 | 23.03 | 14.43 |

TABLE V: Results of action anticipation on the test sets of EPIC-Kitchens. The test set is divided into kitchens already seen S1 or unseen S2 from the model. The table confirms also on the test set that our smoothing labels procedure can improve performances of the state-of-the-art model RU-LSTM.

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Fig. 4: Qualitative results of our smoothing labels procedure. We show the comparison between the top-10 predictions of our model at $\tau_a = 1$ second trained either with smoothed labels or with one-hot vectors. These examples are from the validation set where both the models predict correctly, under the top-5 accuracy, the upcoming action. The model trained on one-hot labels is more confident and tries to concentrate all the prediction energy on a very restricted set of actions, without capturing the uncertainty of the future. By contrast, smoothing labels shape the prediction distribution considering similar actions to the ground truth.

(a) GloVe Smoothing Matrix. (b) Verb-Noun Smoothing Matrix. (c) Temporal Smoothing Matrix.

Fig. 5: Smooth Labels Matrices. Each matrix represents the prior component for the label smoothing procedure reported in Eq. (3) and each row corresponds to a single label prior. In the GloVe and Verb-Noun priors can be recognized squared structures on the diagonal because the labels are alphabetically ordered. The Temporal prior has sparse row entries since there is no major occurrence trend or structure in the training set.

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