Abstract

In this report, we describe the technical details of our submission to the EPIC-Kitchens Action Anticipation Challenge 2022. In this competition, we develop the following two approaches. 1) Anticipation Time Knowledge Distillation using the soft labels learned by the teacher model as knowledge to guide the student network to learn the information of anticipation time; 2) Verb-Noun Relation Module for building the relationship between verbs and nouns. Our method achieves state-of-the-art results on the testing set of EPIC-Kitchens Action Anticipation Challenge 2022.

1. Introduction

EPIC-KITCHENS is a large annotated egocentric dataset [1, 2]. Action anticipation is an important task in EPIC-KITCHENS.

We summarize our main contributions as follows:

1) Aiming at the problem that the missing information of anticipation time affects the performance of egocentric action anticipation, we propose Anticipation Time Knowledge Distillation (ATKD) to distill the information of anticipation time.

2) Because of the lack of consideration of the relationship between verbs and nouns in the existing research work on Egocentric Action Anticipation, we propose a Verb-Noun Relation Module (VNRM) to model the relationship between verbs and nouns.

3) Our approaches show superior results on EPIC-KITCHENS-100.

2. Our approach

2.1. Base Model

We use Causal Transformer Decoder (like AVT-h) [5] as base model. We use a 4-head, 4-layer model as our baseline.

2.2. Anticipation Time Knowledge Distillation (ATKD)

The temporal gap between the past observations and the future action (Anticipation Time) [4, 12] will result in missing information. To solve the problem that the missing information of anticipation time, we propose a knowledge distillation method to distill the information of anticipation time. Fig. 1 shows the student model. We initialize the future video embedding with the learnable parameter. Fig. 2 shows the overview of Anticipation Time Knowledge Distillation. The input of the teacher model is full video and the input of the student model is the concatenation of the observed video and future video embedding. In the teacher...
model, if there are no labels in the anticipation time clip, we use the label of the closest labeled clip as its label. The teacher model can distill the soft label of anticipation time to the student model.

Finally, we use a multi-scale block to improve the performance. Fig. 3 shows the architecture of student model with multi-scale block. Fig. 4 shows the details of multi-scale block.

![Figure 2. Overview of Anticipation Time Knowledge Distillation.](image)

![Figure 3. Student model with multi-scale block.](image)

![Figure 4. Multi-scale block.](image)

2.3. Verb-Noun Relation Module (VNRM)

Inspired by [10] and [11], we propose a verb-noun relationship interaction module to model the relationship between verbs and nouns. The module guides the features of the nouns interacting with the wearer in the observed videos to represent the features of the nouns interacting with the wearer in the future through the features of the predicted future verbs. Fig. 5 shows the overview of Verb-Noun Relation Module.

The same as Anticipation Time Knowledge Distillation, if there are no labels in the clip, we use the label of the closest labeled clip as its label.

Finally, we use knowledge distillation to improve the performance. The input of the teacher model’s verb branch is the full video and the input of the teacher model’s noun branch is only the observed video.

2.4. Feature Extraction

We use some action recognition models as backbones to extract features.

The backbones are as follow:

- **Model A** SlowFast 16×8, R101+NL[3], predicting verb and noun
- **Model B** SlowFast 8×8, R101[3], predicting verb and noun
- **Model C** TSN(BNInception)[4, 9]
- **Model D** Mformer-L[7], with temporal stride 4
- **Model E** Mformer-HR[7], with temporal stride 8
- **Model F** Mformer-HR[7], with temporal stride 4
- **Model G** SlowFast 16×8, R101+NL[3], predicting verb, noun and action
- **Model H** SlowFast 8×8, R101[3], predicting verb, noun and action

2.5. Ensemble

We use an ensemble of a set of 10 models as final result for testing set.

3. Experiments

3.1. Implementation Details

We train the networks using AdamW[6], using a batch size of 128, label smoothing[8] of 0.4, an l2 weight decay of
$5e - 4$, and an initial learning rate of $1e - 4$. The maximum number of training iterations is set to 300 epochs. A cosine annealing with a warm-up restart schedule (20 cycles) is used. The cycle is set to 15 epochs with 1 epoch of linear warmup. All 10 models which we use as an ensemble for the testing set are trained on the same hyperparameters with the same random seed.

Table 1. Results of ablation studies (Anticipation Time Knowledge Distillation).

| Method       | KD   | Multi-Scale | Backbone | Backbone(teacher) | Verb | Noun | Action |
|--------------|------|-------------|----------|-------------------|------|------|--------|
| Base Model   | F    |             |          |                   | 32   | 32.3 | 15.9   |
| ATKD         | ✓    | ✓           |          |                   | 32.2 | 35.3 | 17.3   |
| ATKD         | ✓    | ✓           |          |                   | 31.7 | 36.4 | 18.1   |
| ATKD         | ✓    | ✓           |          |                   | 31.7 | 36.3 | 19.1   |

Table 2. Results of ablation studies (Verb-Noun Relation Module).

| Method       | Backbone | Backbone(teacher) | Verb | Noun | Action |
|--------------|----------|-------------------|------|------|--------|
| Base Model   |          |                   | 32   | 32.3 | 15.9   |
| VNRM(w/o KD) | F        | \               | 33.9 | 34.7 | 16.8   |
| VNRM         | F        | F               | 31.7 | 37   | 17.5   |
| VNRM         | F        | B               | 34.7 | 38.4 | 18.7   |
| VNRM         | F        | B+F(average soft label) | 36.5 | 36.8 | 18.7   |

Table 3. 10 models for ensemble.

| #   | Method       | Backbone | Backbone(teacher) | Verb | Noun | Action |
|-----|--------------|----------|-------------------|------|------|--------|
| 1   | Base Model   |          |                   | 32   | 32.3 | 15.9   |
| 2   | ATKD         | F        | B                 | 33.7 | 36.3 | 19.1   |
| 3   | ATKD         | E        | B                 | 34.5 | 35.6 | 17.3   |
| 4   | ATKD         | A        | A                 | 32.6 | 34.6 | 17     |
| 5   | ATKD         | B        | B                 | 32.6 | 35.4 | 16.9   |
| 6   | ATKD         | F        | \                | 31.2 | 34.6 | 16.7   |
| 7   | VNRM         | G        | G                 | 29.6 | 36   | 16.3   |
| 8   | VNRM         | H        | H                 | 33.1 | 34.4 | 15.9   |
| 9   | ATKD         | D        | B+F(average soft label) | 31.7 | 38.2 | 17.1   |
| 10  | VNRM         | B        | B+F(average soft label) | 32.9 | 39.7 | 19.2   |

Table 4. The result on the testing set (User:hrgdscs).

| Overall | Uncinet | Fail   |
|---------|---------|--------|
| Mean Yp-5 Recall | Mean Yp-5 Recall | Mean Yp-5 Recall |
| Web | Noun | Action | Verb | Noun | Action | Verb | Noun | Action |
| Ensemble | 39.91 | 41.71 | 20.43 | 20.44 | 17.94 | 19.27 | 32.45 | 36.09 | 17.11 |

3.2. Results

The result of the ablation studies can be found in Table 1 and Table 2. The result of 10 models for the ensemble is shown in Table 3.

The final ensemble result on the testing set is presented in Table 4. Our algorithm achieved the best performance.

4. Conclusion

In this paper, we propose two novel methods. The validation and testing results show that our proposed method can achieve excellent performance.

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